EVALUATION OF THE RESIDENTIAL REAL TIME PRICING PROGRAM, 2007-2010

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Acknowledgments

CNT Energy provided bill savings data used in the net benefit assessment. Summary results for bill savings is drawn from the Comverge report, “Com Ed Residential Real-Time Pricing Program 2010 Annual and Full Program Report”.

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1 Executive Summary

The Illinois legislature was one of the first legislative bodies in the U.S. to encourage real-time pricing (RTP) rates for residential customers. Illinois Public Act 94-0977 required that electric utilities which serve more than 100,000 customers must have RTP available to residential customers as a rate option. This Act led to the Illinois Commerce Commission (ICC) Docket 06-0617, which found that a residential RTP program would likely provide a net economic benefit to the residential community as a whole. As part of this docket, the Commonwealth Edison Company (ComEd) received approval to launch in 2007 the Residential Real Time Pricing (RRTP) program.

Residential Real Time Pricing presents to the residential customer "de-averaged" electricity supply prices that are a direct pass-through of PJM hourly prices without mark-up. These prices provide a real-time price signal to customers about the real cost of their electricity use, with day-ahead prices serving as a good signal of prices to expect the following day. The program also provides information regarding opportunities to control electricity bills through energy efficiency and peak load management. A key component of that information is the targeted use of both day-ahead and real-time "high price alerts" via email, text message or phone to alert customers of expected (in the case of day-ahead alerts) and current (in the case of real-time alerts) high prices.

RRTP is an optional program for the ComEd residential customers who participate through the program administrator, Comverge, which is responsible for the on-going development, implementation, operations and marketing of the RRTP program. Marketing tasks include providing existing program participant / prospective participant outreach and assistance, enrollment and education. In 2008, CNT Energy was contracted to help with community based local outreach / marketing. CNT also assists with current participant outreach and education, manages and maintains the program's billing / participant savings tool, and performs various analyses.

Part of ICC Docket 06-0617 was a requirement to perform an economic evaluation of the real-time pricing programs after the end of calendar year 2010 to assess if the program generated net benefits for Illinois residential customers. The purpose of this report is to present the evaluation of these net benefits for the RRTP program, 2007-2010.

The next section presents the summary results of the net benefit assessment. This is followed by a summary of other important findings from this year's impact evaluation of the RRTP program.

1.1 *Summary of Net Benefit Assessment*

The total net benefits for the RRTP program are calculated for three different populations:

1. All PJM customers
2. All ComEd customers
3. ComEd Residential customers

It is important to emphasize that in this report, net benefits refer to net benefits to *energy consumers*. Navigant considers the net benefits that accrue to all PJM customers to be the best indicator of overall economic benefits for consumers from the RRTP program. However, the subset of benefits that accrue only to ComEd residential customers is also reported based on the specific requirements of the ruling from Illinois Commerce Commission (ICC) Docket 06-0617. That docket required an economic evaluation of the real-time pricing program be conducted after the implementation period of 2007-2010, and further required specific identification of the net economic benefits accruing to ComEd's residential customers. In the discussion below, Navigant first reports on the net benefits for the program to date, and then reports on projected savings for the next ten years (2011-2020), assuming RRTP enrollment stays at the current level.

1.1.1 RRTP Program Net Benefits, 2007-2010

Table 1 provides the annual program costs and annual program benefits *to residential ComEd customers*, over the first four years of the program, 2007–2010. There are dramatic changes in program net benefits from year to year. In the start-up years of the program, net benefits are negative: -$1,933,000 in 2007 and -$1,701,000 in 2008. This reflects the significant investment needed to develop the processes and IT systems required for program start-up, and the cost of recruiting new customers into a new program. In 2009 and 2010 these start-up costs dissipate and therefore net benefits increasing substantially as more customers join the program. The overall effect is the achievement of positive net benefits of $24,000 in 2010. It deserves emphasis that this net benefit assessment of the first four years of the program applies to ComEd residential customers only, as required in Docket 06-0617. After three years of strong investment in program start-up costs and experimentation with different marketing methods, the program shows positive net benefits in the fourth year.

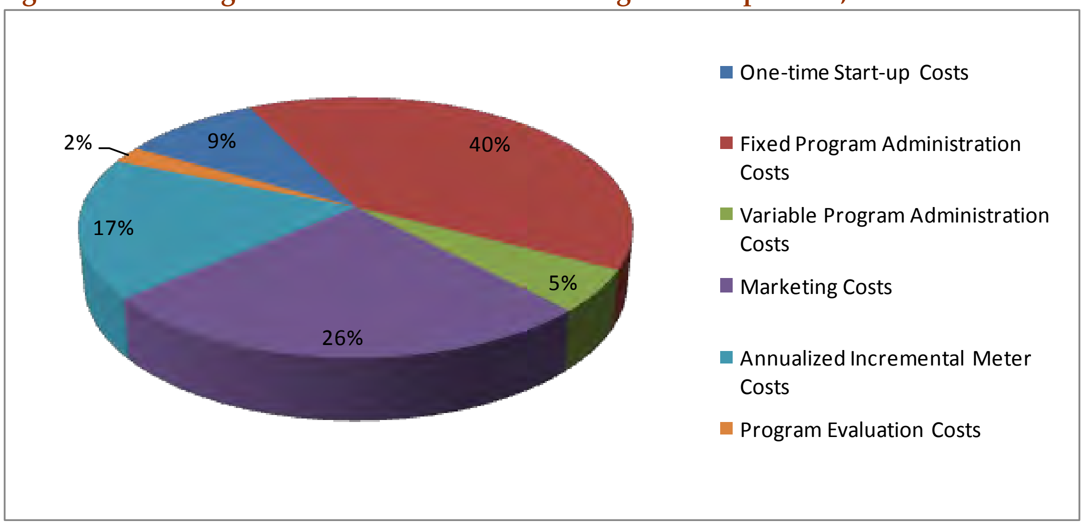
Figure 1 presents the percentage allocation of costs across program components for the four years of the program. As indicated in the discussion above, the cost allocation varies from year to year, but the figure gives a general sense of the relative costs of program components.

Table 1. Historical Benefits and Costs for RRTP Program 2007-2010

	2007	2008	2009	2010
Participant Benefits: Avoided Capacity Costs	$17,000	$138,000	$187,000	$353,000
Participant Benefits: Consumer Surplus	$245,000	$425,000	$1,639,000	$2,170,000
Non-Participant Benefits: Residential Customers	$34,000	$73,000	$86,000	$83,000
TOTAL BENEFITS	$296,000	$636,000	$1,912,000	$2,606,000
TOTAL COSTS	$2,229,000	$2,337,000	$2,696,000	$2,582,000
NET BENEFITS	**-$1,933,000**	**-$1,701,000**	**-$784,000**	**$24,000**

Program start-up costs and incremental meter costs are included.
Source: Navigant analysis

Figure 1. Percentage Allocation of Costs across Program Components, 2007-2010



1.1.2 RRTP Net Benefits, Inception through 2020

The historical analysis leads to the question of what program net benefits would be if the program were extended into the future. Table 2 provides the present value of program net benefits that would accrue were the RRTP program extended another ten years, covering the period 2007–2020. Benefits are calculated at three levels: benefits to all PJM customers, benefits to all ComEd customers, and benefits to all ComEd residential customers. The RRTP program generates positive net benefits of $12,210,000 at the PJM level, but negative net benefits when the population of interest is restricted to ComEd customers. The best measure of the net benefit of the RRTP program to energy consumers, while accounting for costs incurred by ComEd, is the PJM-level measure.

A key assumption in this assessment of the net benefits to ComEd's customers is that the relationship between PJM's real-time prices and ComEd's fixed-rate prices become perfectly aligned in the future (no forecast error). For the historical period covered by this analysis, PJM's real time prices were somewhat lower than ComEd fixed-rate prices. If the average difference between PJM's real time prices and ComEd's fixed-rate energy prices that existed in the program period 2007-2010 persists over the 10 year forecast period, the RRTP program would generate *positive* net benefits to ComEd customers generally and to ComEd *residential* customers in particular. This result is revealed in a series of sensitivity analyses, as indicated below.

Table 2. Net Present Value of Benefits and Costs for Program, Inception through 2020

	PJM View	ComEd View	ComEd Residential Customer View
Participant Benefits: Avoided Capacity Costs	$6,171,000	$6,171,000	$6,171,000
Participant Benefits: Consumer Surplus	$11,099,000	$11,099,000	$11,099,000
Non-Participant Benefits: Market Effects	$22,650,000	$3,295,000	$1,022,000
TOTAL BENEFITS	$39,920,000	$20,565,000	$18,292,000
TOTAL COSTS	$27,710,000	$27,710,000	$27,710,000
NET BENEFITS	**$12,210,000**	**-$7,145,000**	**-$9,418,000**

These net benefits reflect a base scenario where RRTP participants in 2010 continue on the program until 2020, but there are no additional participants added to the program.
The societal discount rate is 1%.
Program start-up costs and incremental meter costs are included.
In all future years the energy component of the flat rate is perfectly balanced with hourly prices (zero forecast error).
Hedging Premium is 10%.
NPV are calculated as the mean of 14 iterations of different weather scenarios over the forecasted years.
Source: Navigant analysis

1.1.3 Sensitivity Analysis of Forecasted Net Benefits

A series of sensitivity analyses were conducted on key assumptions in the net benefits model to examine the effect of the assumptions on forecasted net benefits. To summarize:[1]

- If the average forecast error between PJM's real time prices and ComEd's fixed-rate prices that existed during the program period 2007-2010 persists over the 10-year forecast period, the RRTP program would yield positive net benefits to ComEd customers generally and to ComEd *residential* customers in particular. The net benefits for all ComEd customers would be $3.79 million, and the net benefits for ComEd's residential customers would be $1.52 million.
- Allowing RRTP program participation to grow substantially from 2011-2015 increases overall net benefits to PJM customers, but the effect on ComEd customers is mixed, reducing net benefits (making net benefits more negative) for growth to 25,000 participants, and increasing net benefits –in particular, causing net benefits to increase to +$770,000 over the forecast period 2011-2020—for growth to 50,000 participants. As explained in the body of the report, this nonlinearity in the effect of enrollment growth is due to quasi-fixed costs.

[1] All results reported here apply to the present value of net benefits over a program period of 2007-2020.

- As expected, increasing the societal discount rate to 3 percent reduces net benefits when they're positive (PJM-level analysis) and increases net benefits when they're negative (both ComEd-level analyses).
- Excluding start-up costs increases net benefits at all levels by about $900,000.
- The value of the hedging premium has a substantial impact on the present value of net benefits. At the PJM level an increase in the hedging premium from 5% to 15% increases net benefits from $8.9 million to $15.5 million. If the assessment is restricted to ComEd residential customers net benefits also increases considerably, but stay negative, increasing from -$12.7 million to -$6.1 million.
- Excluding incremental meter costs causes a substantial increase in net benefits, causing the net benefit to ComEd residential customers to rise from the base case of -$9.4 million over the 2007-2020 program period to +$107,000.

1.1.4 Additional perspective on net benefits

Two additional points about the net benefit results deserve emphasis. First, a trade-off occurs between non-participant benefits and participant benefits, depending on the relationship of market energy prices to the fixed-rate price. In years like 2008 when market prices are relatively high, non-participants gain larger benefits because load reductions due to the program generate relatively large energy price reductions along the "steep" (inelastic) portion of the supply curve[2]. Participants, on the other hand, receive lower bill savings. Alternatively, in years like 2009 and 2010 when market prices are low compared to the fixed-rate price, non-participant benefits from the program are relatively low because load reductions due to the program generate relatively small energy price reductions along the "flat" (elastic) portion of the supply curve, but participant bill savings are relatively high. In short, when non-participant benefits are high, participant benefits are low, and vice versa.

Second, there are a number of potential program benefits identified by Navigant that were not included in the net benefits assessment because they are too difficult to quantify reliably without considerable resources. These include benefits associated with improvements in electricity markets –namely, improved power quality and reliability, lower price volatility, and market power mitigation –that could prove significant in certain circumstances, but which are unlikely to be substantial in the case of the RRTP program due to current market conditions and the small size of the program. A change in either the size of the program or the conditions of the market could create a situation in which these benefits are substantial and warrant efforts to carefully quantify.

RRTP program benefits also include health and environmental benefits. For instance, using existing peer-reviewed studies, Navigant approximated the benefit of the RRTP program in reducing SO_2, NO_x, and CO_2 emissions to be about $185,000 per year. Navigant has not included this value in its net benefit assessment because the recipients of these benefits are not necessarily ComEd customers or residential customers in the PJM market.

[2] In Table 1, non-participant benefits in 2008 appear to be slightly *less* than in subsequent years. But this benefit was obtained with a much smaller RRTP enrollment –roughly half of the 2010 level. It follows that if enrollment in 2008 equaled that of 2010, nonparticipant benefits in 2008 would have been roughly twice the value in Table 1.

1.2 *Other Findings of the Effect of the RRTP Program*

The primary objectives of this evaluation were to determine the net benefits of the RRTP program, and to investigate how RRTP participants respond to the program. We now address several issues concerning this second objective.

1.2.1 Conservation effect: Do RRTP participants reduce overall energy use?

The main purpose of allowing the price of electricity faced by residential consumers to fluctuate hourly is to promote demand response (shifting of energy use), not necessarily energy conservation (reduction in total energy use). A program designed to induce consumers to practice more energy conservation would require that the price of electricity become generally higher, as opposed to the RRTP program in which the price faced by participants is sometimes higher and sometimes lower than that paid by non-participants. Nonetheless, conservation effects are possible. Navigant used fixed effects regression analysis of the monthly bills of RRTP households before and after enrollment, with households in the ComEd Residential Load Study (RLS) serving as controls, to estimate conservation effects.

Results are reported in Table 3. The RRTP program has indeed generated energy conservation in all seasons, with conservation highest in summers and averaging 4% annually. In a statistical analysis of hourly load shapes using very different data and statistical modeling, Navigant found similar levels of energy conservation.

Table 3. Conservation Impact of RRTP Program on RRTP Participants[a]

Season	Overall Percentage Impact	Average daily kWh Impact	Average Seasonal Impact (kWh)
Summer	-5.0%	-1.86	-171
Spring	-2.4%	-0.58	-54
Autumn	-4.8%	-1.28	-117
Winter	-3.2%	-1.04	-94
Annual Impact	**-4.0%**	Average Annual Savings (kWh)	**-435**

[a]These results apply to RRTP households that are not enrolled in ComEd energy efficiency programs; *Source: Navigant analysis*

1.2.2 Hourly load shapes: Do RRTP participants shift hourly energy consumption?

Even in the absence of conservation effects a dynamic pricing program can generate substantial economic benefits by inducing households to shift consumption from high-priced hours to low-priced hours. Navigant investigated this issue using hourly regression models applied to interval data for both RRTP and RLS households. Unlike the analysis of program conservation effects, the analysis could not use a difference-in-difference approach to isolate the effect of the RRTP program on hourly consumption because interval data for RRTP households are not available for the period before households entered the RRTP program. Instead, Navigant used a propensity score matching method to match each RRTP household to an RLS household, with the matched RLS household thereby serving as a control for the RRTP household. The basic regression model was run separately for all 24 hours of a day, for weekdays vs. weekends, and for each full season of the RRTP program. The model distinguishes the effect on consumption of a household's "membership" in various subgroups of the RRTP program; in particular, whether the household was enrolled to receive, via email or text message, real-time price alerts at the 10-cent threshold (RT-10 household) or the 14-cent threshold (RT-14 household), or not at all (PA household[3]), and whether it was enrolled in ComEd's Load Guard program at the 10-cent threshold or the 14-cent threshold.[4, 5]

Figure 2 presents typical load shapes derived from the analysis, and Figure 3 presents how energy consumption by RRTP households differs from baseline consumption –that is, consumption predicted for RRTP households in the absence of the RRTP program. Each figure includes mean hourly real-time prices to show the relationship between loads and prices. Overall, results of the analysis indicate the following:

1. Even on days without high price alerts or Load Guard events, RRTP households shift their consumption to avoid high prices.
2. RT-10 households are generally more responsive to the program than RT-14 or PA households; RT-10 households exhibit greater load-shifting on non-event days and a greater response to price alerts. This is not surprising in light of the fact that the default price alert is the 14-cent alert, and RRTP households that desire alerts at the 10-cent level must request the change. Taking such a step is evidence of program engagement.
3. In general, RT-14 households are not responsive to RT-14 alerts;
4. In 2008, day-ahead alerts generated at best a slight average hourly reduction in household energy consumption. There have been no day-ahead alerts since 2008.
5. RT-10 alerts generate small hourly savings among RT-10 households, on the order of 0.0-0.08 kW, during mid afternoon to early evening hours. There is no good statistical evidence that alerts called outside of these hours generate savings.
6. There is no strong evidence that RT-14 alerts generate savings among RT-14 households.
7. Load Guard events at the 10-cent threshold generate small reductions in energy consumption in the event hours. Load Guard events at the 14-cent threshold generally do not generate statistically significant reductions in event hours. The relatively small energy savings directly attributable to Load Guard events as compared to what is frequently found for DLC programs likely is due to the fact that RRTP customers have already made a substantial shift in energy consumption away from peak hours.

[3] "PA" stands for "Passive Alert"; PA households are not actively engaged in the high price notifications via email or text message, but can stay informed of high price notifications via the RRTP program web page, www.thewattspot.com.

[4] The Load Guard program is a direct load control program available only to RRTP households enrolled in ComEd's AC cycling program.

[5] In August 2010, 57% of RRTP households were RT-14 households not participating in Load Guard; 29% were PA households not participating in Load Guard; 7% were RT-10 households not participating in Load Guard; and the remainder (7%) were in Load Guard and receiving either RT-10 or RT-14 alerts.

Figure 2. Hourly Load Shapes and Hourly Mean Price, Summer 2010, Weekdays, Non-event days

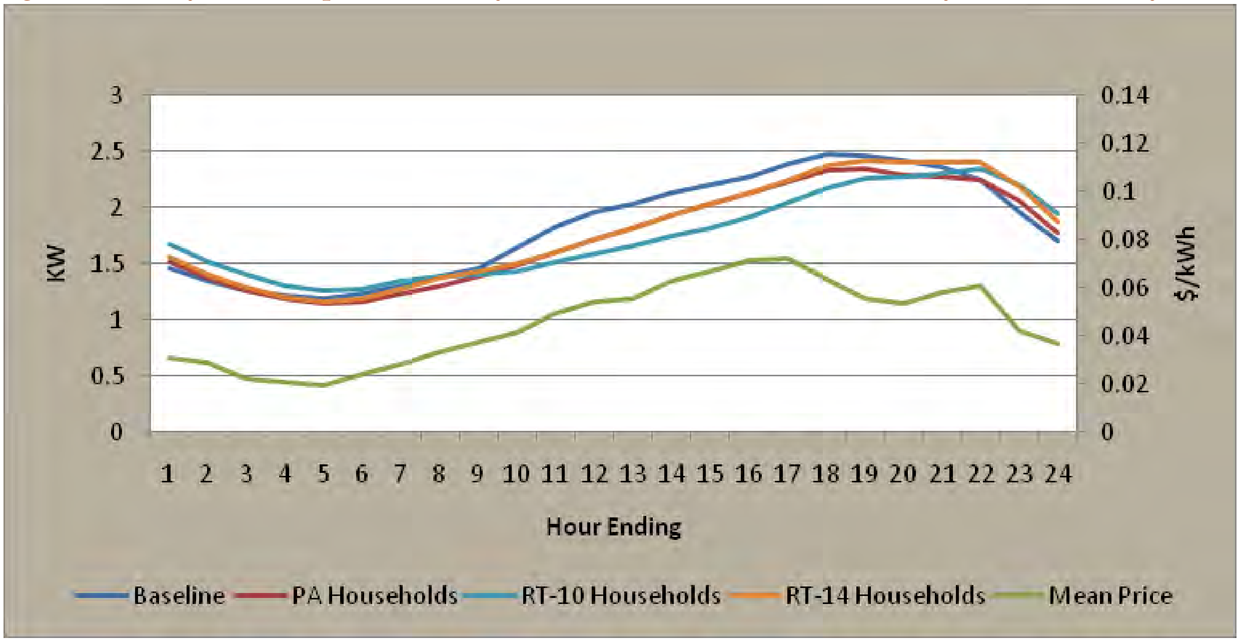
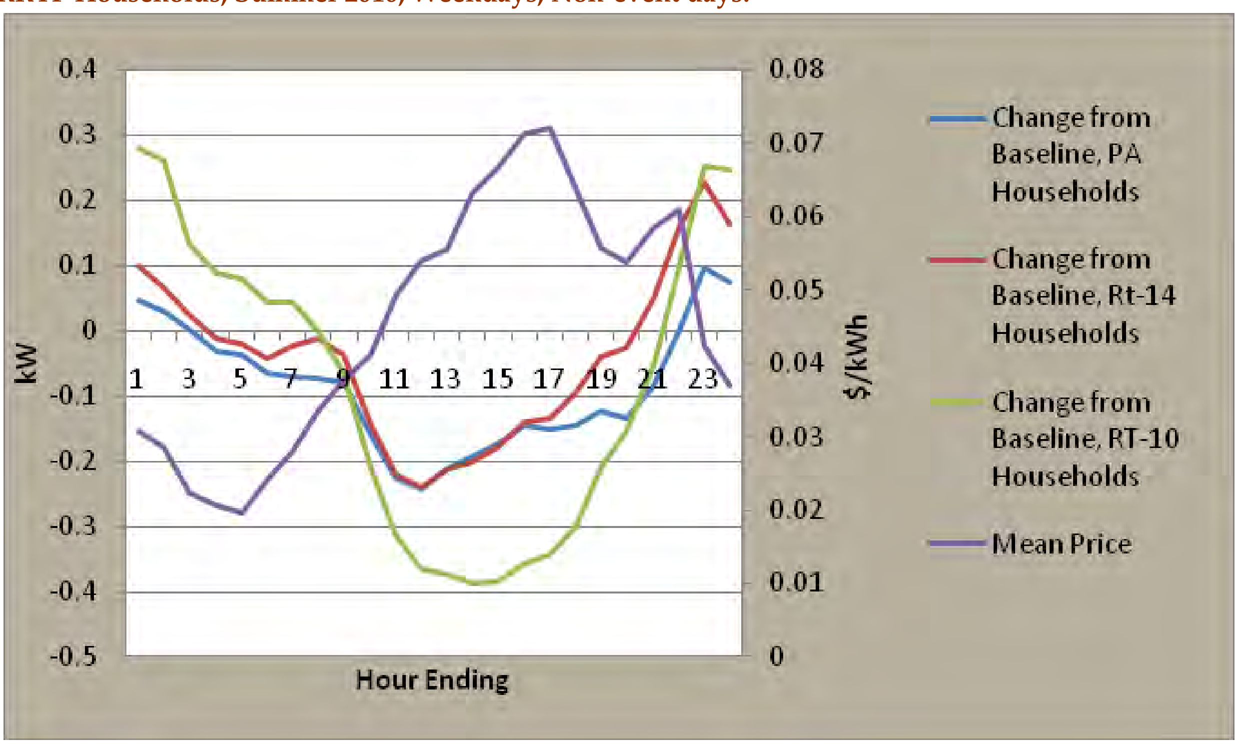


Figure 3. Hourly Mean Price and Mean Change from Baseline Hourly Energy Consumption by RRTP Households, Summer 2010, Weekdays, Non-event days.



1.2.3 Price elasticity of demand: How responsive are RRTP participants to price changes?

Navigant models price responsiveness among RRTP participants as reflecting a medium-run price response and a short-run price response.

In the medium run, households respond to differences in *average hourly price* with a broad shift in energy consumption behavior as compared to their behavior under the fixed-price regime, forming new habits and modes of operation, such as running dishwashers at night. Such broad shifts in behavior are consistent with the information provided to RRTP customers, indicating that shifting energy consumption to overnight hours, when prices are low, reduces energy bills.

Even after shifting their daily energy consumption routine to exploit variation in average hourly prices, households can potentially benefit still more **in the short run** –on an hour-to-hour basis—by responding when prices deviate significantly from their hourly means.

Navigant measured medium-run elasticities for the summer season only, because evidence from the analysis of hourly load shapes indicated little, if any, price-responsiveness by RRTP households in the other seasons. Medium-run elasticities are measured using regression analysis based on the relationship between *average* hourly prices and *average* hourly deviations in consumption from baseline, where baseline consumption is derived from the consumption behavior of RLS matched control households. In general the analysis yielded the result that medium-run elasticities are higher for RT-10 households than for RT-14 households, and are higher on weekdays than on weekends. For RT-10 households, medium-run elasticities averaged about -0.15, indicating that a 1% increase in the average price in an hour reduces consumption by 0.15%, or, to put it another way, an increase in the average price in an hour by 10% reduces average consumption in the hour by 1.5%. For RT-14 households, medium-run elasticities average about -0.05.

The extent of the short-run price response depends on both the extent of the price deviation and the cost of short-term behavioral adjustments, including the cost of closely monitoring prices. Frequently checking electricity prices is time consuming, and the potential gains from doing so are quite small. Navigant therefore expects RRTP households to exhibit systematic price responsiveness primarily on days when the cost of price information is low and the potential benefits are high. Such is exactly the case on days with either day-ahead or real-time price alerts. On such high price alert (HPA) days, participants are alerted that prices are high, creating an opportunity to lower their bill by reducing their load during the high-priced hours.

Not all RRTP households make short-run adjustments to prices, even on HPA days. The analysis of hourly load shapes indicated that RT-10 households are responsive to RT-10 alerts, whereas RT-14 are not responsive to RT-14 alerts, and of course PA households are not directly alerted at all about high prices. In light of these observations, Navigant limited its analysis of short-run price responsiveness to the consumption behavior of RT-10 households on the 112 HPA days in the summer months of 2007-2010.

Short-run demand for energy was modeled using the Generalized Almost Ideal (GAI) demand system approach, in which energy demand is modeled as the demand for a set of distinct time-indexed goods. Estimates of short-run own-price elasticities ranged from a low about -0.16 in the hours of 9 AM -2 PM, and again from 4-5 PM, to a high of -0.31 from 3-4 PM. These elasticities reflect the responsiveness of RT-10 households to real-time prices at different times of day on high-price days. So, for instance, a 10% increase in price at 3-4 PM of a high-price day reduces energy consumption at 3-4 PM by 3.1%.

1.2.4 Bill savings: do RRTP households save on their electricity bills?

Aggregate bill savings for RRTP participants in 2010 were $1,936,844, which amounts to 13% of the aggregate electric bill. Aggregate savings for the four years of the program were $3,954,862, which also amounts to 13% of the aggregate electric bill. In 2010, 89% of RRTP households enrolled in the RRTP program reaped positive savings, with mean savings of $177.

2 Introduction

This report presents results of an evaluation of the effect of the Residential Real Time Pricing (RRTP) program from its beginning in 2007 through the end of 2010. The introduction begins with a recounting of background information on the potential benefits of real-time pricing rate designs, and a description of the unique characteristics of the RRTP program. This is followed by a presentation of basic program statistics to provide a broad overview of the past 4 years of the program, a discussion of the evaluation objectives, and a summary of the organization of the remainder of the report.

2.1 The Potential Benefits of Real-Time Pricing

Electricity prices are among the most volatile of any market commodity. Driving this volatility is the fact that electricity cannot be stored in significant quantities. As a result, during periods of high demand (hot summer days for example), hourly electric prices can vary substantially over just a 12-hour period. On extreme days, price spikes during resource constrained periods can see increases of 100 fold or more if there is not enough demand-side response to mitigate the system and supply-side factors that are driving prices up. These extremely high prices, even though they may occur only during a few hours each summer, can represent a substantial cost to all the customers in the regional electricity market.

While the costs of electricity in wholesale markets can vary dramatically, retail pricing, particularly for residential and small commercial customers, has largely remained subject to regulated tariffs. These tariffs typically have provided customers with fixed rates, i.e., they pay the same price for electricity regardless of when and how much is used. This fixed rate does not reflect the true cost to the economy of consuming electricity at a given point in time, and therefore it distorts key market decisions.

An important near-term challenge facing electricity markets is the rational pricing of retail electricity. The goal of any market — regulated or unregulated — is to allocate resources equitably, promote efficient investment, and provide incentives for innovation. Prices provide the market signals that are used to allocate resources. Specifically, the key is to appropriately price what is scarce. For electricity markets, what is scarce is on-peak energy. If the market is not designed to appropriately price what is scarce, the market will not be efficient and disconnects between demand and supply can occur, resulting in price spikes. Clearly, non-time-differentiated electricity rates cannot reflect the true costs at the wholesale level of on-peak electricity. With standard rates, customers have no idea what the actual cost of electricity is at any given time and they are not able to make choices regarding conserving a scarce resource. As a result, they cannot make decisions regarding the appropriate use of electricity required for an efficient market.
Innovative pricing, such as real-time pricing (RTP), is one method of allowing for the interaction of demand and supply needed for efficient markets. Research on time-differentiated pricing is growing as the benefits of these pricing options are becoming better recognized. These options allow customers to see the real wholesale costs of electricity and make decisions regarding their energy use based on market conditions. Overall, customers who see real prices and adjust their demand in

response to these price signals can make the electricity system more efficient and stable. As a result, retail electric prices that better reflect the costs of obtaining power in wholesale markets can provide benefits to electricity markets, including the following:

- **Increased system reliability** as price mitigates demand when resources become scarce.
- **Reductions in costs** of electricity to all customers in a regional market as a result of better management of scarce supplies and reductions in capital costs incurred to meet peak demands.
- **Risk management** by allowing customers to manage a portion of the electricity price and commodity risks and be compensated for this service.
- **Environmental benefits** by promoting efficient use of resources and price signals to manage demand.
- **Customers benefit** from being on an RTP rate since now their ability to use electricity flexibly across on-peak and off-peak periods is valued, i.e., a key attribute of their energy use – flexibility in time-of-use – is given a value.
- **Market power mitigation** by providing a demand response to offset high prices for generated electricity.
- Providing the **incentives for innovation** needed to create technologies and value propositions for load management and peak demand response.
- RTP better reflects the actual cost of service, allowing a **more equitable distribution of costs** across customers and customer classes.
- Unlike conventional load control or curtailable/interruptible incentives, dynamic tariffs such as RTP can be made **available to all customers,** regardless of usage level or appliance ownership.

These potential benefits from RTP options can accrue to a number of entities:

- **Participants.** RTP participants can benefit by having the ability to make more informed choices regarding how they use electricity. This provides them the opportunity to lower their monthly bills.
- **Electricity customers not participating.** The RTP rate can also benefit all customers (participants and non-participants) in a regional electricity system because a relatively small fraction of price-responsive demand can have sizeable impacts on market-wide price spikes and electric system efficiency.
- **Utilities.** Utilities can benefit through load reductions on their delivery network during peak periods, and delaying or avoiding the need to make additional capital investments.

Recognition of these potential benefits has led to a number of pilot programs and a move towards time-differentiated rates for large customers. The Illinois legislature was one of the first legislative bodies to encourage real-time pricing rates for residential customers. Illinois Public Act 94-0977 required that electric utilities which serve more than 100,000 customers must have RTP available to residential customers as a rate option. This Act led to the Illinois Commerce Commission (ICC) Docket 06-0617, which found that a residential RTP program would be likely to provide a net economic benefit to the residential community as a whole. As part of this docket, Commonweatlh Edison Company (ComEd) received approval to launch Residential Real Time Pricing (RRTP).

2.2 *About the Residential Real Time Pricing (RRTP) Program*

ComEd's RRTP program evolved from a four-year experimental rate, RATE RHEP (Residential Hourly Electric Pricing), and has been expanded by the signing into law of State Senate Bill 1705; Public Act 94-0977. This law requires, among other things, that Illinois utilities with more than 100,000 customers must provide a residential real-time pricing program for up to four years, beginningin 2007. The program is optional and available to all ComEd residential customers. Customers can enroll online, by completing and sending enrollment authorization forms, or by calling the program administrator's call center.

Upon enrolling in the program, RRTP participants agree to pay an additional monthly $2.25 Participation Fee (which essentially is a reduced meter lease fee for the special metering required for hourly pricing). Participants also agree to remain in the RRTP Program for at least twelve (12) consecutive months, as required in Section 16-107(b-5). These two requirements are set forth in the Illinois Commerce Commission's Final Order in ICC Docket No. 06-0617. The Meters are read manually every month and customers cannot review their hourly usage until the end of their monthly billing cycle.

Electricity bills include three broad categories of charges: Electricity Supply Services, Delivery Services, and Taxes/Other. With one exception, all charges in these latter two categories are the same for ComEd's RRTP participants and for fixed-price rate customers. The exception is the $2.25 per month meter lease charge on RRTP bills. Otherwise, the difference between the bills for RRTP households and households on the standard fixed-rate price involve components of Electricity Supply Services. In particular, RRTP households face differences in the Electricity Supply Charge, the Transmission Services Charge, and the Purchased Electricity Adjustment Charge that arise because electricity supply for RRTP customers is procured differently than it is for fixed-rate customers.

The program administrator, Comverge, is responsible for the on-going development, implementation, operations and mass marketing of the RRTP program, which includes providing existing program participant / prospective participant outreach and assistance, enrollment and education. In 2008, CNT Energy was contracted to help with community based local outreach / marketing. CNT also assists with current participant outreach and education, manages and maintains the program's billing / participant savings tool, and performs various analyses.

ComEd enlisted several means to aid RRTP program participants in reducing their energy consumption during peak price hours. These include the targeted use of "high price alerts" via email or phone on the evenings before expected high price days, as well as price alerts in hours where prices exceed threshold levels. In particular, the program includes:

- Day-Ahead High Price Notifications (hereafter referred to as "Day Ahead alerts" or simply DA alerts). These are triggered by PJM's day-ahead market prices, and apply to hours for which the day-ahead LMP price exceeds the price threshold, which was 13 cents per kWh until June 2008, and is now 14 cents. Notification is by email, SMS text message or automated phone call. It is important to emphasize that the RRTP program does not bill participants based on day-ahead prices. DA alerts are used to give participants an indication of the real-time hourly prices to expect the following day.

- Real-Time "Day-Of" High Price Notifications. These are triggered when PJM's LMPs reach or exceed a specified price threshold for 30 consecutive minutes (six consecutive 5-minute real-time prices). Current thresholds are 10 cents and 14 cents per kWh. The default threshold –the threshold to which an RRTP household defaults if it does not specifically choose a threshold—is 14 cents. Alerts are by email or SMS text message. RRTP households that do not provide an email address can check for alerts on the program web portal, www.theWattSpot.com. Hereafter we refer to real-time price notifications at the 10-cent level as "RT-10 alerts", and we refer to real-time price notifications at the 14-cent level as "RT-14 alerts".

Another program option for RRTP customers is the Load Guard Load Automated Price Response Service. This is open to RRTP participants also enrolled in ComEd's Central AC Cycling program. It allows RRTP participants to choose a real-time hourly price (10 cents or 14 cents per kWh) at which they want their AC to automatically cycle off and on every 15-minutes over a 2-hour period. Hereafter we refer to Load Guard events at the 10-cent threshold as "LG-10 events", and we refer to Load Guard events at the 14-cent threshold as "LG-14 events".

2.3 Basic Statistics Relevant to RRTP Program

Impacts of the RRTP program depend on four key factors: program enrollment, hourly temperature, energy prices, and RRTP events (DA alerts, RT-10 alerts, etc.). Data for each of these factors is presented and summarized below.

2.3.1 Program Enrollment

Figure 4 presents net enrollment in the RRTP program, and in the various sub-programs, from January 2007 through August 2010. Abbreviations for membership in the various sub-programs used in Figure 4 and throughout this report are the following:

- RT-10 household: an RRTP household enrolled to receive RT-10 alerts;
- RT-14 household: an RRTP household enrolled to receive RT-14 alerts;
- PA household: an RRTP household that does not receive any alerts via email or text messaging; such households can receive "passive alerts" (thus "PA") via the program website;
- LG-10 household: an RRTP household enrolled in the Load Guard program at the 10-cent threshold;

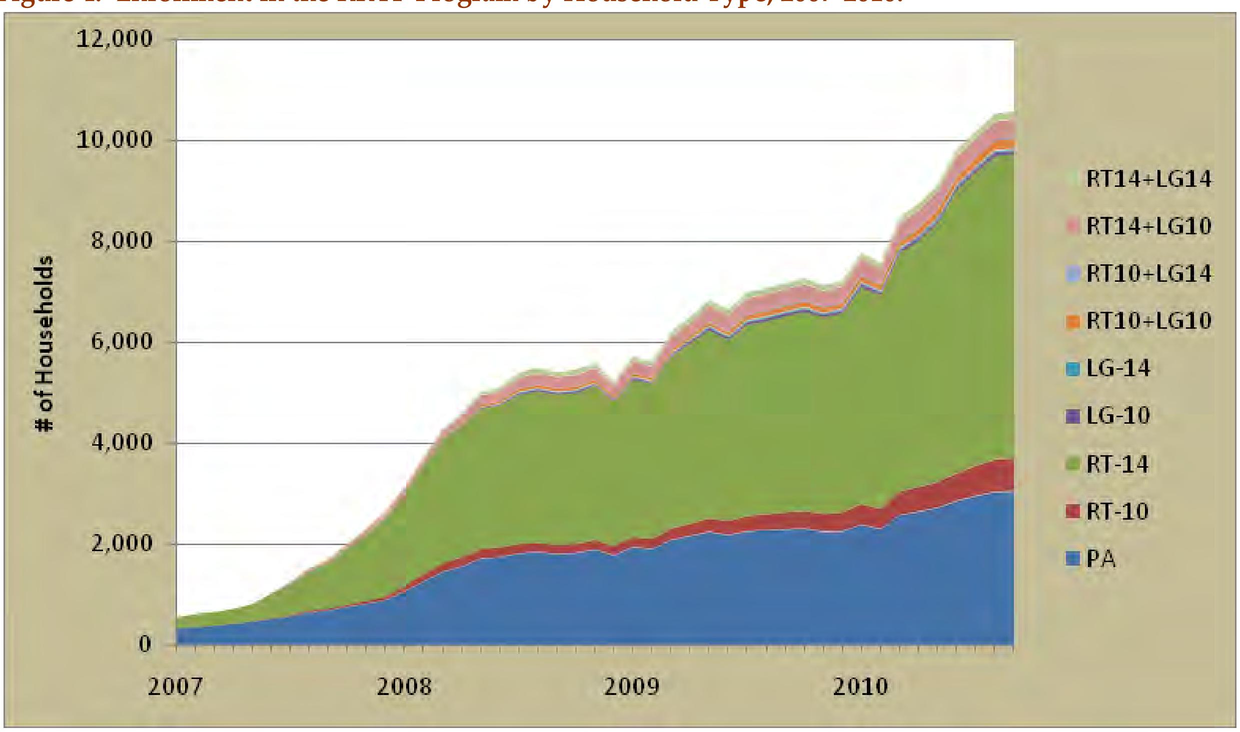
- LG-14 household: an RRTP household enrolled in the Load Guard program at the 14-cent threshold.

Households receiving alerts *and* enrolled in Load Guard are referenced by concatenating subprogram abbreviations, such as "RT10 + LG14".

Figure 4 reveals the following:

- Enrollment climbed steeply through early 2008, increased at a lower rate in 2009, and climbed steeply again in 2010. As discussed below, summer 2009 was an especially cool summer with low energy prices.
- The majority of RRTP participants (57.0% in August 2010) are RT-14 households, with PA households –households that are not contacted about price alerts, and are not enrolled in Load Guard –composing a sizable minority of households (28.9% in August 2010);
- Relatively few households receive RT-10 alerts or are enrolled in the Load Guard program (in August 2010, 6.1% of households are RT-10 households, and 6.9% of households are enrolled in the Load Guard program at either the 10-cent or 14-cent threshold).

Figure 4. Enrollment in the RRTP Program by Household Type, 2007-2010.



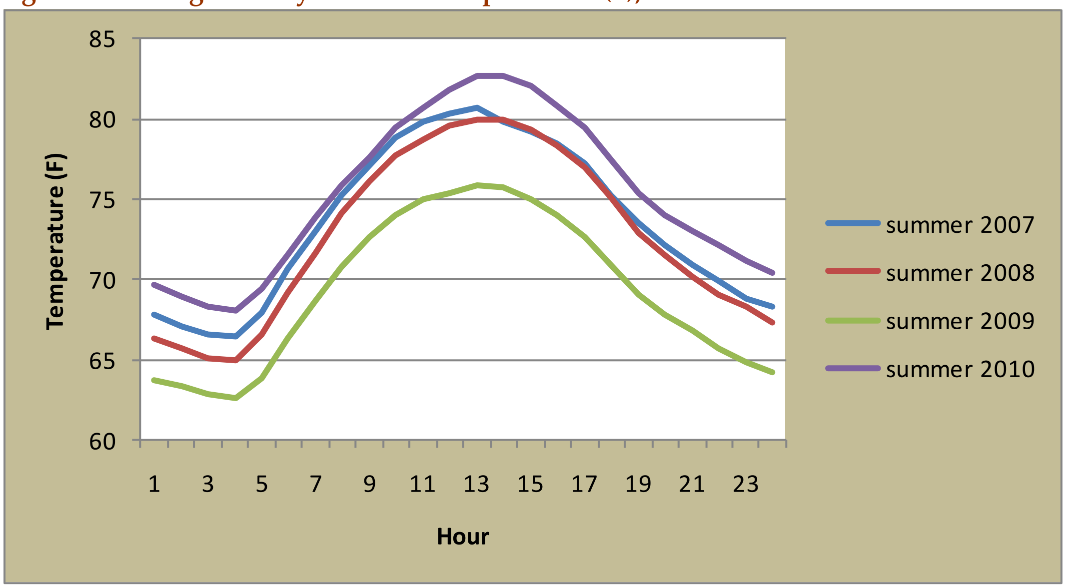
Source: Navigant analysis

2.3.2 Temperature

Figure 5 presents average hourly summer temperatures for 2007-2010. The average number of cooling degree days at Chicago O'Hare airport is 676; cooling degree days in summers 2007-2010 were 810-719-499-974. The upshot is that summer of 2008 was close to normal, summer 2009 was exceptionally cool, and summer 2010 was much warmer than average.

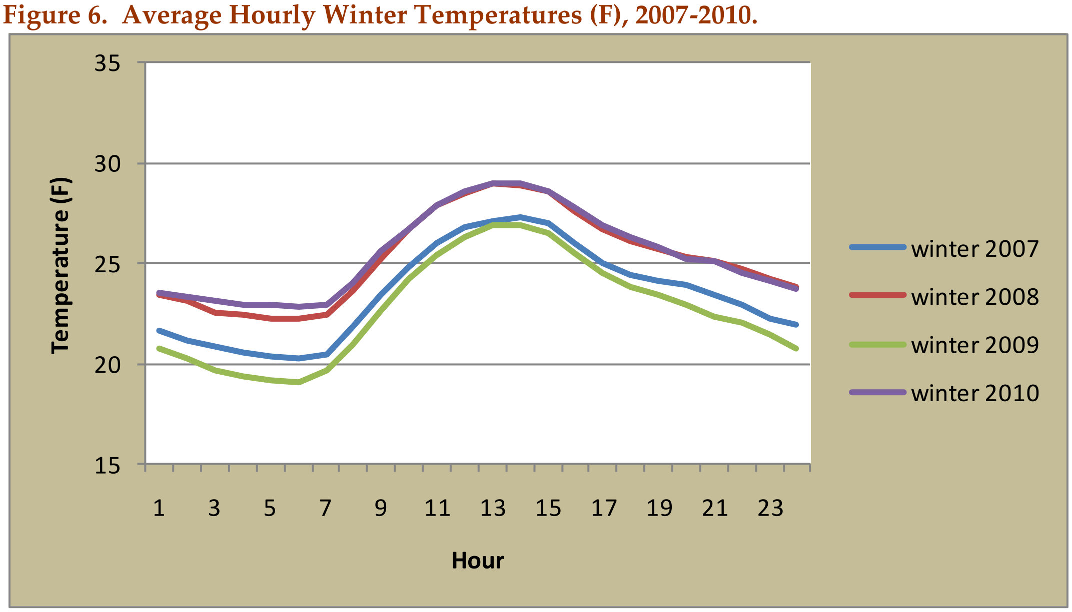
Figure 6 presents average hourly winter temperatures for 2008-2010, the three full winters of the program. Winters 2008 and 2010 were very similar, with winter 2009 markedly cooler. Average heating degree days for winter at Chicago O'Hare is 3555; heating degree days in winters 2008-2010 were 3625-3818-3582, indicating that the winters of 2008 and 2010 were essentially normal, and winter 2009 was colder than average.

Figure 5. Average Hourly Summer Temperatures (F), 2007-2010.



Source: Navigant analysis

Figure 6. Average Hourly Winter Temperatures (F), 2007-2010.

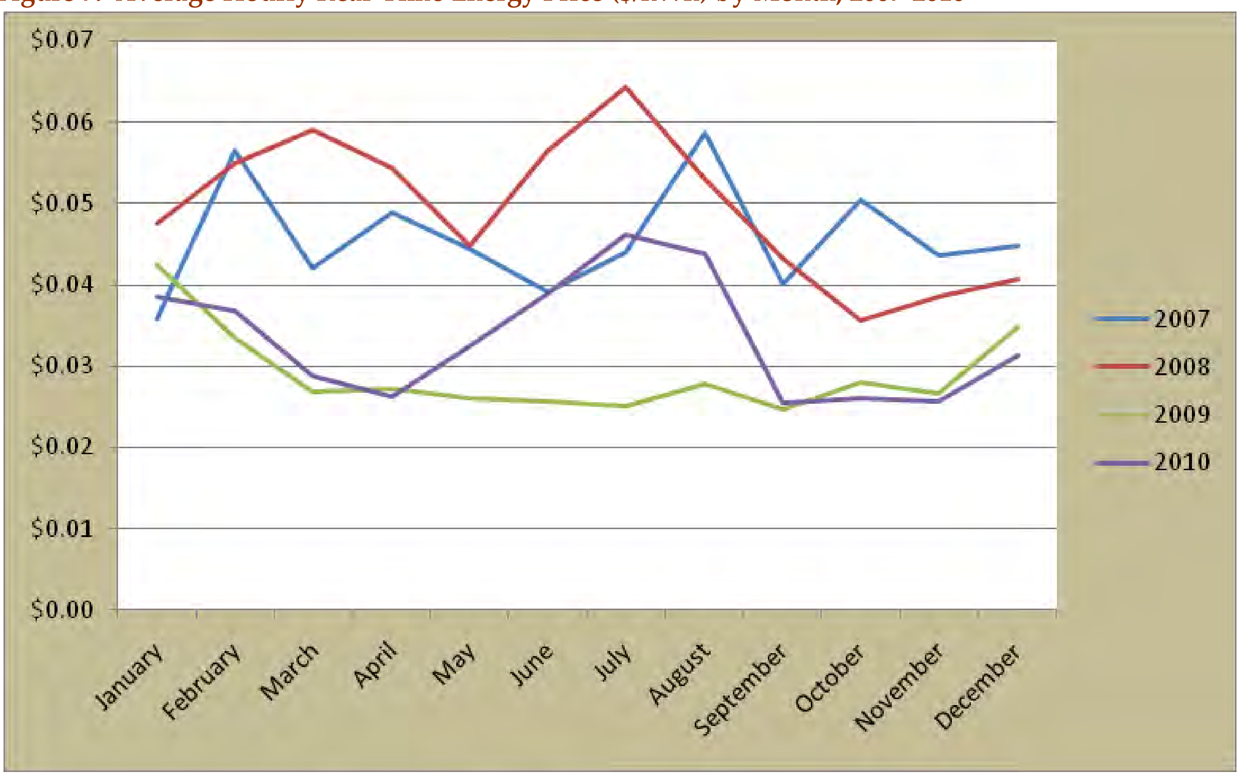


Source: Navigant analysis

2.3.3 Energy Prices

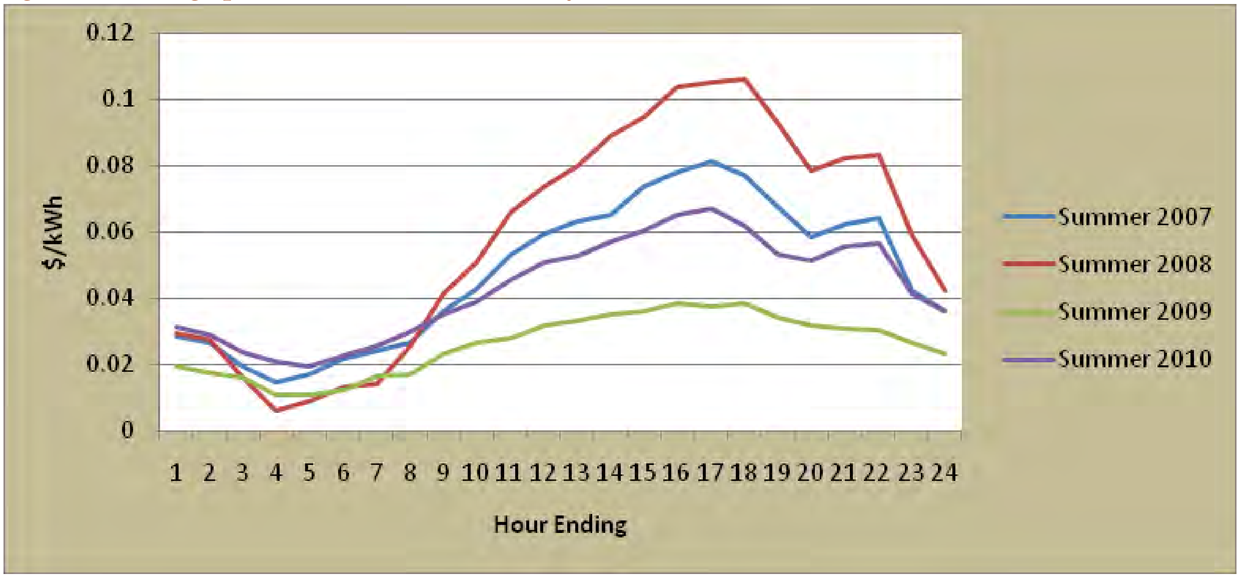
Figure 7 shows average real-time energy (LMP) prices during the program period, 2007-2010; Figure 8 shows average price for each hour of the day in the program summers; Figure 9 shows the same for the three full winters of the program; and Figure 10 presents the distribution of hourly energy prices within each year of the program period. The figures emphasize that prices were highest in summer 2008, even though, as discussed above, summer 2008 was only slightly above normal, indicating that high prices were largely supply-driven. On the other hand, the low prices in summer 2009 were largely demand-driven, as summer temperatures were far below normal. The high prices in winter 2008 were most likely both demand driven (due to below-average temperatures) and supply driven.

Figure 7. Average Hourly Real-Time Energy Price ($/kWh) by Month, 2007-2010



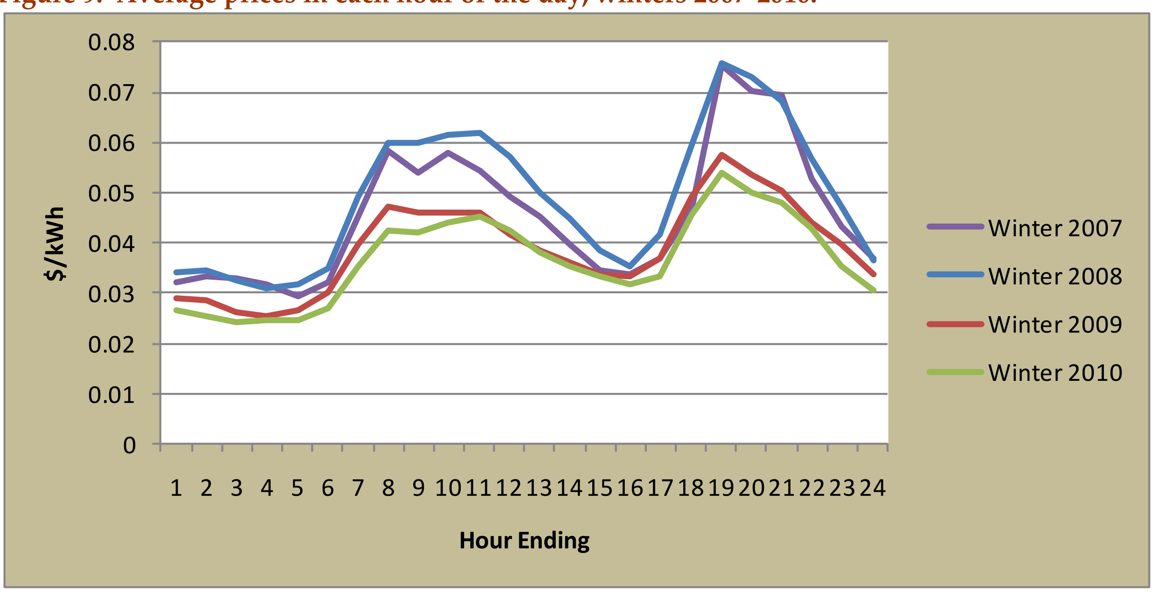
Source: Navigant analysis

Figure 8. Average prices in each hour of the day, summers 2007-2010.



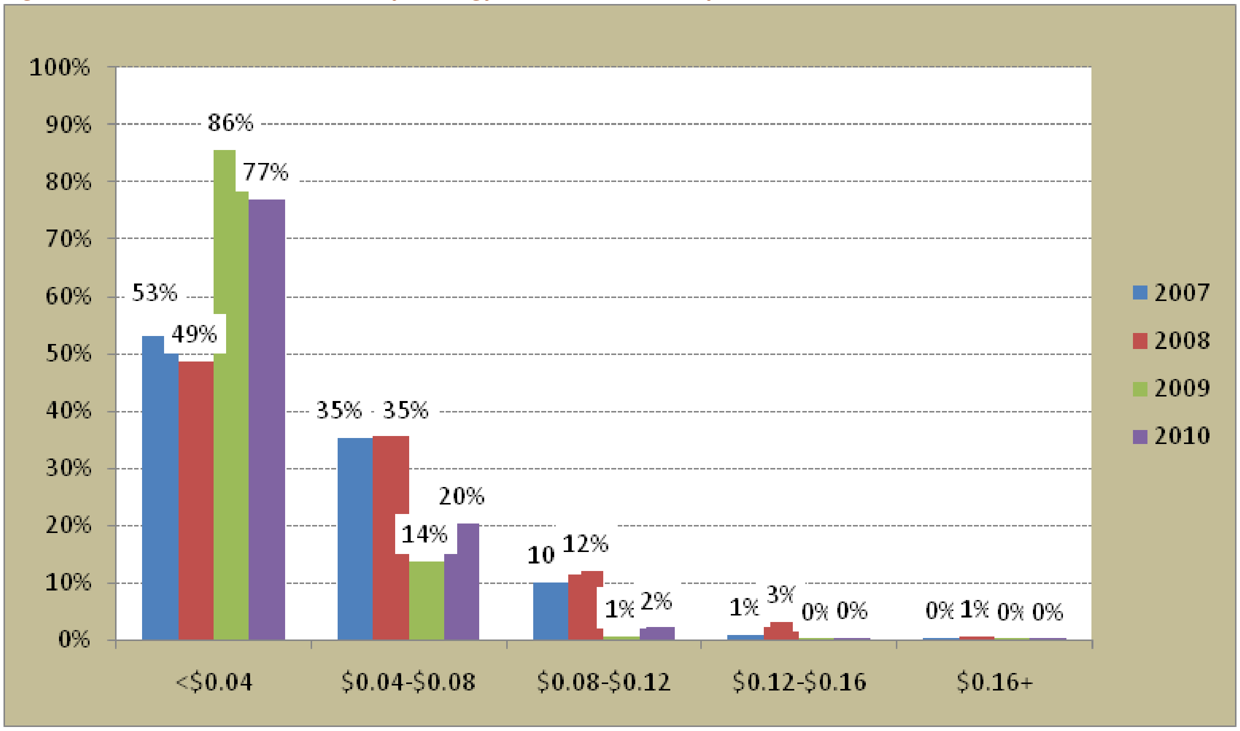
Source: Navigant analysis

Figure 9. Average prices in each hour of the day, winters 2007-2010.



Source: Navigant analysis

Figure 10. Distribution of Hourly Energy Prices ($/kWh) by Year, 2007-2010.



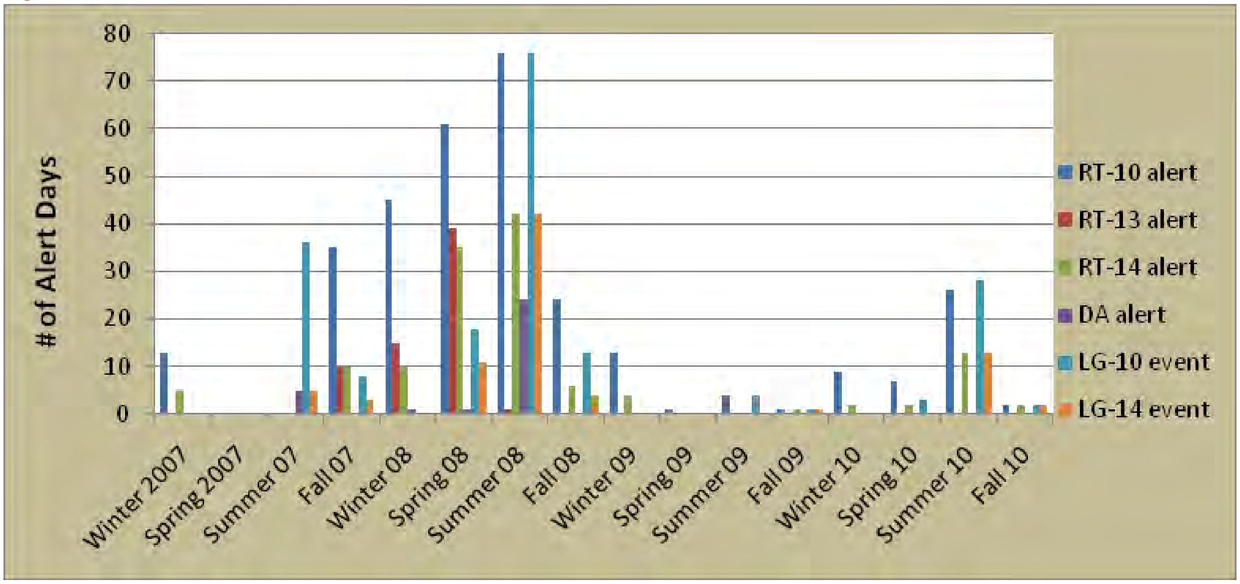
Source: Comverge Analysis

2.3.4 Event History

Figure 11 shows the RRTP event history. Several features of the event history stand out:

- Spring and summer 2008 had by far the most events, due to high energy prices in this period;
- There are relatively few high-price alerts in winters, the exception being the winter of 2008, when prices were much higher than usual (see Figure 9);
- The most common events were RT-10 and LG-10 events, which naturally coincide;
- Day-ahead alerts have not been called since summer 2008;
- Because summer 2009 was much cooler than average, there were almost no events;
- RT-13 alerts were replaced by RT-14 alerts in the summer of 2008.

Figure 11. RRTP Events, 2007-2010.



Source: Navigant analysis

2.4 Evaluation Objectives

There are two objectives for the impact evaluation of the RRTP program. The first is to establish how RRTP participants respond to the program, and includes the following components:

- Conservation effect – Does participation in the RRTP program reduce overall energy use?
- Hourly energy demand shifting– In addition to any conservation effects, does the RRTP program cause participants to shift behavior from some hours of the day to others? If so, across which hours? Does the shifting vary by season? Is it affected by the high-price alerts and/or participation in the Load Guard program?
- Price elasticity of demand – To the extent that the program induces energy demand shifts across hours, does this shifting correspond to hourly changes in prices? If so, what is the price elasticity of demand?
- Bill savings – How much do participants actually save on their electric bills?

The second objective is to assess the net benefits of the program *to energy consumers*. Meeting this objective relies on the analyses engendered by the first objective, as well as analyses concerning program costs, the effect of the program on market energy prices, and the economic measurement of program benefits to participants. A prominent feature of the net benefit assessment is a simulation module that allows investigation of how key modeling assumptions affect the estimate of program net benefits.

2.5 Report Organization

Section 3 of this report addresses the first category of objectives described above. It begins with an examination of the conservation effect of the RRTP program, then addresses the shifting of consumption across the hours of the day, then examines the price responsiveness of program participants, and concludes with a discussion of the impact of the program on bill savings.

Section 4 presents the estimation of economic net benefits from the program. It begins with a discussion of the estimation of marginal cost curves necessary to calculate the effect of the program on market prices and thus on nonparticipants, and then discusses how program costs, program benefits to participants, and program benefits to non-participants are combined to generate estimates of the net benefit of the program.

Section 5 presents conclusions and recommendations.

Finally, the appendices present supporting details of analyses conducted in the evaluation.

3 Program Impacts for 2010

In this section of the report we address the issues associated with the first objective identified in section 2.4 –how RRTP participants respond to the program. Subsection 3.1 concerns program conservation effects. Subsection 3.2 concerns hourly impacts –in particular, load-shifting impacts of the program. Subsection 3.3 concerns the price responsiveness of RRTP participants –whether, in other words, any observed load-shifting across hours corresponds to high and low prices. Such price responsiveness is manifest in the price elasticity of demand for energy. The last subsection of the chapter presents bill savings generated by the program.

3.1 Conservation Effects

The main purpose of allowing the price of electricity faced by residential consumers to fluctuate hourly is to promote demand response (shifting of energy use), not necessarily energy conservation (reduction in total energy use). A program designed to induce consumers to practice more energy conservation would require that the price of electricity become generally higher[6], as opposed to the RRTP program, in which the price faced by participants is sometimes higher and sometimes lower than that paid by non-participants. Nonetheless, it is possible that RRTP customers conserve energy compared to what they would have consumed in the absence of the program, and in this section we statistically investigate this possibility.

Also investigated is how the RRTP interacts with other ComEd energy efficiency programs to generate energy conservation. The question examined is whether joint participation in the RRTP program and existing ComEd energy efficiency programs generates savings that are greater (or less) than the sum of their individual savings. In this analysis, Navigant examines the interaction of the RRTP program with ComEd's Appliance Recycling and Central AC Efficiency programs.

For the analysis, Navigant used available monthly consumption data for RRTP households and a set of control households drawn from ComEd's Residential Load Study (RLS). Table 4 provides basic data on the study period and sample size for the analysis. In light of these statistics –in particular, that the study period extends across substantial variations in weather—Navigant believes the estimated average conservation impacts are quite robust.

Table 4. Customers in Sample Used to Examine RRTP Conservation Effect[a]

	Number of Customers	Date of First Observation	Date of Last Observation
Control Group (RLS Households)	4,569	3-Jan-05	28-Oct-10
RRTP Participants	12,116	3-Jan-05	28-Oct-10

[a]The number of customers is the gross number of customers in each group. Due to customers entering and leaving the groups, in any given season the number of customers is less than this number; see, for instance, Figure 4 in subsection 2.3.1. *Source: Navigant analysis*

[6] That is, the average annual or monthly price for the same amount of consumption would need to go up.

3.1.1 Methodology

The conservation impact was estimated using seasonal fixed effects regression models of household energy consumption. Fixed effects models can be used with data in which observations over a sample of households are available over a period of time (what econometricians call "panel data"). This allows the inclusion in the model of household-level constants—the fixed effects—instead of a single constant, as in ordinary least squares analysis. Including such fixed effects provides a considerable statistical advantage. In their absence, the analyst must take care to include as regressors all those time-invariant household and housing characteristics—the presence of central A/C, the type of heating system, the size of the residential structure, and so forth—that *might* be correlated with the regressors of interest, such as the indicator variable for enrollment in the RRTP program. Failure to account for these characteristics risks generating biased coefficient estimates, and, ultimately, biased estimates of conservation effects. The fixed-effects model sweeps all of these characteristics into a household-level constant, thereby circumventing this bias issue. In an opt-in program like the RRTP program there remains the potential for selection bias because customers that enroll may not be representative of the general residential population. The fixed-effects model significantly controls for bias in program effects *conditional* on enrollment in RRTP.

Four models were estimated, one for each season. The regression model of household energy consumption is a semi-log model in which the dependent variable is the log of daily average energy consumption for the bill period.[7] Conservation effects are derived from the effect of the RRTP program on average daily energy consumption. The initial model took the form,

$$\begin{aligned}\ln y_{it} &= \alpha_i + \beta_1 CDD_{it} + \beta_2 HDD_{it} + \beta_3 RRTP_{it} + \beta_4 \left(RRTP_{it} \cdot CDD_{it}\right) + \beta_5 \left(RRTP_{it} \cdot HDD_{it}\right) \\ &+ \beta_6 EE_{it} + \beta_7 \left(RRTP_{it} \cdot EE_{it}\right) + \beta_8 \left(RRTP_{it} \cdot CDD_{it} \cdot EE_{it}\right) + \beta_9 \left(RRTP_{it} \cdot HDD_{it} \cdot EE_{it}\right) \\ &+ \beta_{10} LG_{it} + \beta_{11} \left(RRTP_{it} \cdot LG_{it}\right) + \beta_{12} \left(RRTP_{it} \cdot CDD_{it} \cdot LG_{it}\right) + \beta_{13} \left(RRTP_{it} \cdot HDD_{it} \cdot LG_{it}\right) + \varepsilon_{it}\end{aligned} \quad (1)$$

,

where:

y_{it} =	Customer *i*'s average daily consumption (kWh) in billing period *t*;
α_i =	Customer *i's* fixed effect;
CDD_{it} =	The average number of cooling degree days per day experienced by customer *i* in billing period *t;*
HDD_{it} =	The average number of heating degree days per day experienced by customer *i* in billing period *t;*
$RRTP_{it}$ =	A dummy variable equal to one if customer *i* is participating in the RRTP program during billing period *t*;
EE_{it} =	A dummy variable equal to one if customer *i* is participating in either ComEd's Appliance Recycling or Central AC Efficiency program during billing period *t*;

[7] A semi-log model is one in which the dependent variable – the variable on the left-hand side of the equation – is the natural log of the behavior of interest and the independent variables on the right-hand side of the equation are not natural logs. This is to capture the hypothesized non-linear relationship between the independent and dependent variables.

LG_{it} = A dummy variable equal to one if customer *i* is participating in ComEd's Load Guard program during billing period *t*;

The various interactions terms account for the possibility that the effect of the RRTP on household energy consumption depends on weather conditions and household participation in other programs. For example, the term $RRTP_{it} \cdot CDD_{it}$ accounts for possibility that the effect of RRTP enrollment on monthly energy consumption depends on the cooling degree days for the month. The term $RRTP_{it} \cdot CDD_{it} \cdot EE_{it}$ goes further, accounting for the possibility that this CDD-related effect depends on whether the household is enrolled in either the Appliance Recycling or Central AC Efficiency programs.

The semi-log form implies that the marginal (incremental) effect of the various explanatory variables is proportional to consumption: $\partial y_{it} / \partial x_{it} = \beta_x y_{it}$. So, for instance, the effect of a 1-unit increase in CDD on monthly consumption for a household consuming 30 kWh per day and not enrolled in the RRTP program or any other programs is $30 \cdot \beta_1$, while the effect were the household enrolled in the RRTP program, but no other programs, is $30 \cdot (\beta_1 + \beta_4)$, and the effect were the household enrolled in the RRTP program *and* the Load Guard cycling program is $30 \cdot (\beta_1 + \beta_4 + \beta_{12})$.

The inclusion of the dummy variable EE is to account for the participation of RRTP customers in other ComEd energy efficiency programs. ComEd provided Navigant with the customer account numbers and the first date of energy efficiency program participation for each RRTP participant and control group member, by program. The inclusion of the dummy variable LG accounts for the participation of RRTP participants in the Load Guard program. The numbers of participants in the Load Guard program, the Appliance Recycling program and the Central AC Efficiency program are presented in Table 5 below.

Table 5. Participation in ComEd Conservation Programs

		EE Programs		Load Guard
		Appliance Recycling	Central AC Efficiency	
Control Group (RLS Households)	Number	10	2	0
	% of all Control	0.2%	0.0%	0%
RRTP Participants	Number	226	43	955
	% of all RRTP	1.9%	0.4%	7.9%

Source: Navigant analysis

3.1.2 Results

It has been the convention in many impact evaluations of demand response and conservation technologies and pricing schemes, when estimating those impacts with a semi-log model to report the parameter estimates of dummy variables – such as the RRTP participation dummy variable – as the percentage impact of the treatment represented by this dummy variable.

Conceptually, however, the parameter estimate represents the impact on the dependent variable of a marginal – or very small – change in the independent variable. Since a dummy variable carries only two possible values by construction, interpreting the parameter estimate in this manner can slightly distort the true estimated percentage impact. Parameter estimates on dummy variables in a semi-log model must therefore be transformed slightly in order to capture the estimated percentage impact of a treatment. Details of this transformation may be found in Appendix B.

Estimation of the model shown above[8] resulted in estimates of all EE and LG interaction terms (and the LG intercept term) which, but for a single seasonal exception, were found to be not statistically significantly different from zero. In addition, further investigation showed that all the interaction terms were jointly statistically insignificant. These two results together imply that:

a. *There is no discernable impact on conservation as a direct result of the interaction between participation in RRTP and participation in the ComEd energy efficiency programs;*

b. *There is no discernable impact on conservation as a direct result of the interaction between participation in RRTP and participation in the Load Guard program , and there is no discernable impact on conservation at all resulting from participation in the Load Guard program.*

It is important to emphasize that due to the nonlinear form of the regression equation, there is an *indirect* relationship between the RRTP and the energy efficiency programs. In particular, the semi-log functional form of the model casts the effect of the RRTP program as proportional to consumption, and so it follows that, insofar as the energy efficiency programs reduce energy consumption (which is the case, as will be shown below), the indirect effect of the energy efficiency programs is to slightly reduce the effect of the RRTP program by lowering overall energy consumption.

The second result – that participation in the Load Guard program does not result in additional energy conservation – is expected. The snapback effect – whereby consumption levels increase above normal in the period directly following an activated curtailment period – are a well-documented phenomenon accompanying all direct load control programs. In order to recover the set point temperature of the home, the previously curtailed air-conditioner must work harder (because of a greater temperature differential between the desired set point and the inside temperature of the home) immediately following the period of curtailment. In at least one case that Navigant is aware of, the snapback effect actually resulted in a net increase in energy consumption.

[8] Parameter estimates for this initial model specification may be found in Appendix A.

Given the non-significance of the Load Guard intercept term and the joint non-significance of all of the Load Guard and Energy Efficiency interaction variables, Navigant determined that the most robust approach was to simplify and re-estimate the model, eliminating variables for which the parameter estimates were not significant individually or jointly.

The simplified model estimated was:

$$\begin{aligned}\ln y_{it} &= \alpha_i + \beta_1 CDD_{it} + \beta_2 HDD_{it} + \beta_3 RRTP_{it} + \beta_4 \left(RRTP_{it} \cdot CDD_{it}\right) + \beta_5 \left(RRTP_{it} \cdot HDD_{it}\right) \\ &+ \beta_6 EE_{it} + \beta + \varepsilon_{it}\end{aligned}$$

All the variables included have the same definitions as above.

The parameters estimated by season are presented in Table 6, below. Standard errors are presented in Table 7, below. Red-shaded cells indicate parameter estimates that are not statistically significant at the any conventional level of significance. Pink-shaded cells indicate parameter estimates that are not statistically significant at the 95% but *are* significant at the 90% level. Note that for ease of reading all parameter estimates and standard errors have been multiplied by 1,000. The true estimated parameters would be obtained by dividing each value by 1,000.

Table 6. Parameter Estimates for Model of Average Daily Consumption[a]

Season	Dependent Variable	Parameter Estimates x 10^3					
		CDD	HDD	RRTP Dummy	RRTP Dummy x CDD	RRTP Dummy x HDD	EE Dummy
Summer	Natural log, average daily consumption by billing period (kWh)	57.905	-8.959	-113.403	6.344	8.980	-41.692
Spring		59.320	16.269	-29.248	18.316	-1.059	-47.002
Autumn		68.169	16.506	-16.488	-1.260	-2.618	-51.016
Winter		-1,101.093	4.954	-98.367	-77.984	1.641	-18.577

[a] All parameter estimates are multiplied by 10^3 for the purposes of legibility. *Source: Navigant analysis*

Table 7. Standard Errors for Model of Average Daily Consumption[a]

Season	Dependent Variable	Standard Errors x 10^3					
		CDD	HDD	RRTP Dummy	RRTP Dummy x CDD	RRTP Dummy x HDD	EE Dummy
Summer	Natural log, average daily consumption by billing period (kWh)	0.461	1.184	8.566	0.801	1.984	9.125
Spring		0.877	0.139	6.515	1.766	0.279	10.293
Autumn		0.592	0.146	5.816	1.223	0.287	10.631
Winter		140.866	0.123	13.369	569.805	0.337	10.778

[a]All standard errors are multiplied by 10^3 for the purposes of legibility. *Source: Navigant analysis*

The estimated impacts are all of the expected sign:

- The parameter estimates for the RRTP dummy variables are negative for all seasons - participation in the RRTP program leads to conservation in all seasons.
- The parameter estimates for the EE dummy variables are negative for all seasons – participation in a ComEd energy efficiency program leads to conservation in all seasons.
- The parameter estimates for CDD are all positive (indicating temperatures over 65F lead to more consumption, on average) in all seasons but winter (when temperatures over 65F lead to far lower energy consumption).
- The parameter estimates for HDD are all positive (indicating temperatures less than 65F lead to more consumption, on average) in all seasons but summer (when temperatures less than 65F lead to less consumption, on average).

In order to calculate the percentage conservation impact of the RRTP program, and thus the average seasonal kWh impact, the average level of heating degree days and cooling degree days to which members of the control and experimental groups were exposed are required. Note that due to inconsistent billing periods across participants, and the fact that participants could begin actively participating in the RRTP program and the two energy conservation programs at different times, the average temperatures to which they were exposed differ somewhat. These are shown in Table 8.

Table 8. Daily Average of Weather Variables by Type of Participant

Average Weather Values for RRTP Households, by Season				
Season	Cooling Degree Days (RRTP)	Heating Degree Days (RRTP)	Cooling Degree Days (RRTP and EE)	Heating Degree Days (RRTP and EE)
Summer	8.57	0.88	8.77	0.84
Spring	1.19	15.83	1.32	14.85
Autumn	1.97	11.43	1.93	10.62
Winter	0.00	39.85	0.00	39.32

Source: Navigant analysis

This weather data, along with the parameter estimates shown above, are used to obtain the estimated percentage impact of the RRTP program on average participant consumption, by season, since the program's inception until late October 2010. Table 9 presents these estimated impacts for RRTP customers not enrolled in one of the ComEd energy efficiency programs, and Table 10 presents them for RRTP customers enrolled in one of these other programs. RRTP participants who were also participating in either the appliance recycling or HVAC programs achieved higher energy savings compared to those in the RRTP program only. This reflects a simple additive effect of the programs.

Table 9. Conservation Impact of RRTP Program on RRTP Participants, 2007-2010

Season	Overall Percentage Impact	Average daily kWh Impact	Average Seasonal Impact (kWh)
Summer	-5.0%	-1.86	-171
Spring	-2.4%	-0.58	-54
Autumn	-4.8%	-1.28	-117
Winter	-3.2%	-1.04	-94
Annual Impact	**-4.0%**	Average Annual Savings (kWh)	**-435**

Source: Navigant analysis

Table 10. Joint Conservation Impact of RRTP and Energy Efficiency Programs on Participants in RRTP and Energy Efficiency Programs, 2007-2010.

Season	Overall Percentage Impact	Average daily kWh Impact	Average Seasonal Impact (kWh)
Summer	-8.9%	-3.27	-301
Spring	-6.9%	-1.60	-147
Autumn	-9.5%	-2.44	-222
Winter	-5.0%	-1.52	-137
Annual Impact	**-7.6%**	Average Annual Savings (kWh)	**-808**

Source: Navigant analysis

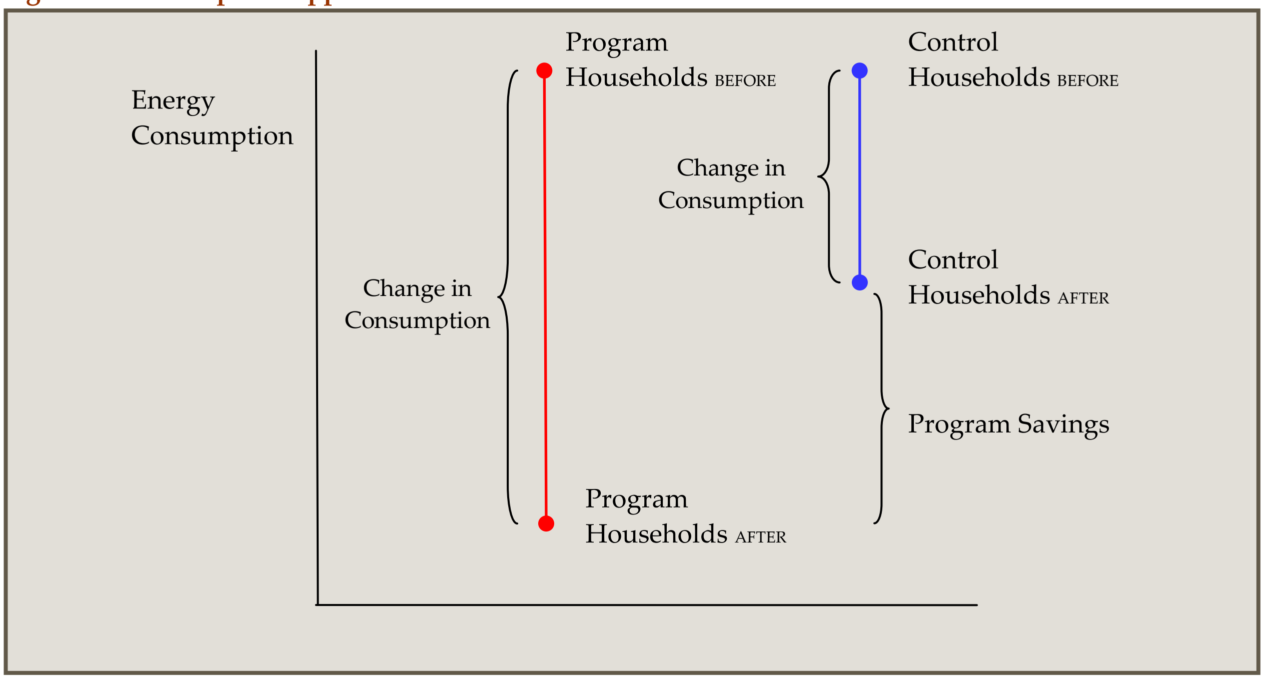
3.2 *Hourly Demand Impacts*

The discussion in the previous section focused on the overall conservation effect of the RRTP program, which masks a potentially major impact of the program: the shifting of consumption by RRTP households over the course of the day from high-price hours to low-price hours, with attendant direct benefits to RRTP households in the form of reduced energy bills, and indirect benefits to non-participant households in the form of changes in local energy prices. The analysis in this section provides estimates of this shifting in energy consumption.

3.2.1 Choosing Control Households for the Hourly Impact Analysis

An important issue in evaluating program effects is the selection of an appropriate control group. To the extent that the control group is not "just like" the treatment group –that is, drawn from the same population—estimation of program effects will be biased unless the analyst controls for differences between the two populations. In the evaluation of conservation effects in section 3.1, Residential Load Study (RLS) households serve as the control group, and the matter of baseline differences in monthly consumption between RLS and RRTP households is addressed via fixed effects regression applied to pre- and post-program monthly bills for both RRTP and RLS households. This approach generates a difference-in-difference criterion for measuring conservation effects: implicitly the analysis generates the differences in monthly consumption by RRTP households before and after entering the program, compares these differences to those generated by control households over the same period, and takes as the program effect the difference (between RRTP and RLS households) in these differences. This approach is conceptually illustrated in Figure 12. Fixed effects regression essentially normalizes the data across RLS and RRTP households to assure that changes in consumption over time are being measured from the same initial position.

Figure 12. Conceptual Approach to Estimation of the Conservation Effect



Source: Navigant analysis

For the analysis of the RRTP program's hourly impacts, there is no hourly consumption data for RRTP households in the pre-program period; we only "see" hourly consumption after enrollment in the program. Consequently fixed effects regression is not possible to address any initial consumption differences between control and program households, because the characteristic of interest –a customer's enrollment in the RRTP program – never changes in the data and therefore would be swept into the fixed effect constant.

To address this issue, we take a two-pronged approach. First, we use the method of *propensity score matching* (PSM) to identify RLS households that match RRTP households in the sense that the RLS households "look like" RRTP households in ways that predict enrollment in the RRTP program. In other words, we attempt to mimic, based on observable variables, an experimental design in which households are randomly assigned to control and treatment (RRTP) groups. Second, in estimating hourly load curves using regression analysis as described below, we include a variable for consumption in the year before the start of the program. To the extent that control households tend to be higher (or lower) consumers of energy than RRTP households, this variable serves as a means of correcting this difference.

3.2.2 The propensity score matching (PSM) method

The PSM method is now common in the economics literature in which program evaluations are conducted with observational, rather than experimental, data.[9] The method estimates the probability that a household is enrolled in the program as a function of observable household characteristics. Conceptually the analyst desires to create the appearance that control and treatment households are randomly assigned; for a participant household that is highly likely to be enrolled in the RRTP program, the analyst identifies a control household with a similarly high likelihood of enrollment; for a participant with a low likelihood, the analyst identifies a control household with a similarly low likelihood. The approach generates an unbiased control sample if enrollment in the program is predicted with random error by the observable variables used in the matching. The method is straightforward:

1. First, a logit regression equation is specified, in which the dependent variable takes a value of 1 if the household is an RRTP household and a value of 0 if it is an RLS household;
2. This dependent variable is regressed on a number of observable variables that are expected to be related to the probability of enrollment.
3. The estimated logit equation is used to predict the probability of enrollment for all households, RRTP and control households alike. This probability is called the household's *propensity score*.
4. For each RRTP household, an RLS match is identified. A variety of matching criteria are possible. For this analysis, we use nearest-neighbor matching on the propensity scores. Specifically, the match to the RRTP household is the RLS household with the propensity score closest to that of the RRTP household.
5. Matches are with replacement; because there are many more RRTP households than RLS households, most control households match multiple RRTP households.

In the PSM exercise used for this analysis, the variables used to predict enrollment are seasonal electricity consumption as reported in monthly bills. Formally, the indicator variable y_i takes a value of 1 if household i is in the RRTP program at some point during the program period, and 0 otherwise. The logit regression equation predicting the probability of enrollment in the RRTP program is,

$$\Pr(y_i = 1) = \frac{e^{\beta \mathbf{x}}}{1 + e^{\beta \mathbf{x}}} \qquad (2)$$

Where β is a set of parameters to be estimated, and the set of explanatory variables $\mathbf{x}$ includes an intercept and the following:

- Average kWh/day in summer 2009, average kWh/day in summer 2010;
- Average kWh/day in winter 2008, average kWh/day in winter 2010;
- The squares of all four of these variables.

[9] See, for instance, Cameron, A. Colin, and P.K. Trivedi, *Microeconometrics: Methods and Applications*, Cambridge University Press, 2005.

We use average daily energy consumption in the summers (June-August) of 2009 and 2010 because these were exceptionally cool and hot summers, respectively. The average number of cooling degree days at Chicago's O'Hare airport is 676; in the summer of 2009 there were 499 cooling degree days, and in the summer of 2010 there were nearly twice that, 974. By contrast, the heating degree days in the winter seasons (December-February) of the program period were fairly uniform, ranging from 3407 to 3818. In the analysis we used the seasons with the middle values for heating degree days, winter 07-08 and winter 09-10, with 3625 and 3582 heating degree days, respectively. The average winter heating degree days at O'Hare is 3555. Logit regression results are presented in Table 49 in appendix A.

3.2.3 Defining the Feasible Set of RSL and RRTP Households for the Analysis

The set of RLS and RRTP households used in the analysis was restricted by the following conditions:

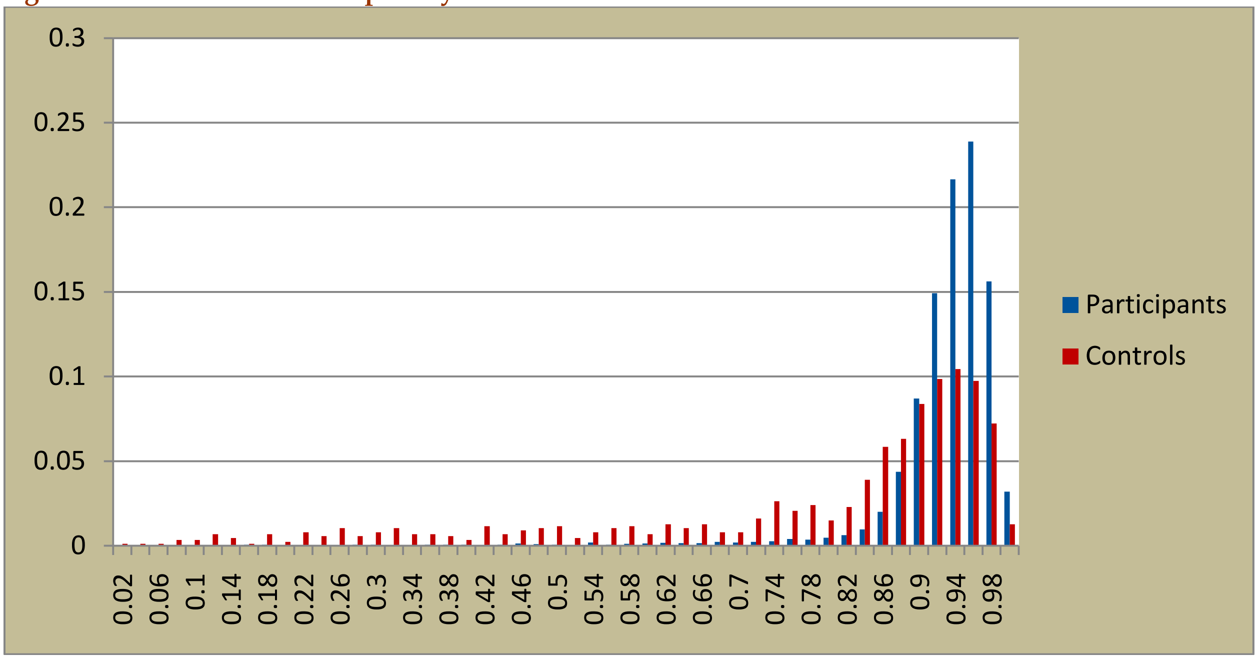
1. RLS accounts must span the program period, 2007-2010. This assures that RRTP households and their matches have the same number of observations in the analysis.
2. The household must have at least three billing records in each of the four seasons used in the propensity score regression. This is to avoid matches that arise due to skewed data, as might arise, for instance, if a household's average daily consumption in the summer of 2010 was due to missing data in the first or last month of a season.

Imposing these conditions yielded a data set for the analysis of 8151 RRTP households, and 872 RLS households available to serve as controls. Consequently the average propensity score is 8151/(8151+872)=90.3%, and the average number of matches per RLS household is 8151/872=9.3.

3.2.4 Summary of PSM results

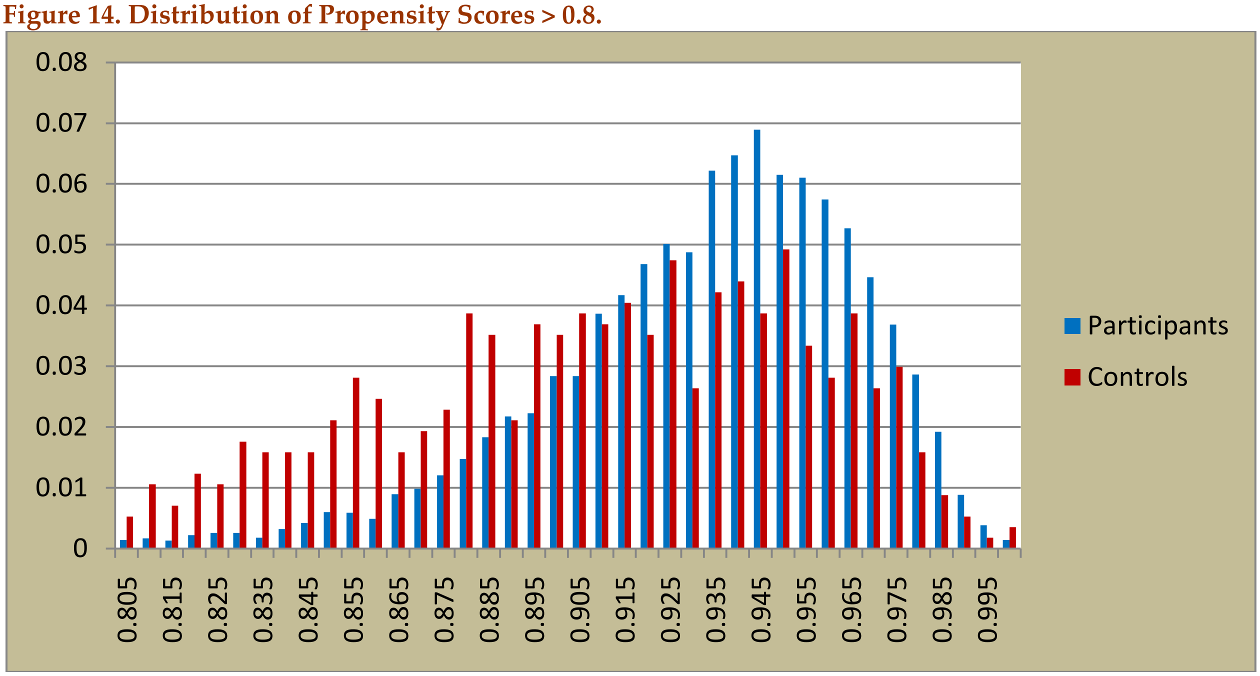
Table 11 presents basic statistics from the matching exercise. Figure 13 presents the distribution of propensity scores for RLS and RRTP households, and Figure 14 gives the distribution *conditional* on having a propensity score of at least 0.8 (80% probability of enrolling in the RRTP program). Results indicate that there are a good number of RLS households with a high probability of enrollment. Figure 15 presents the relationship between an RRTP's propensity score and the closeness of its RLS match. In general the matches are very close, especially for the vast majority of RRTP households with a propensity score between .90 and .98.

Figure 13. Distribution of Propensity Scores



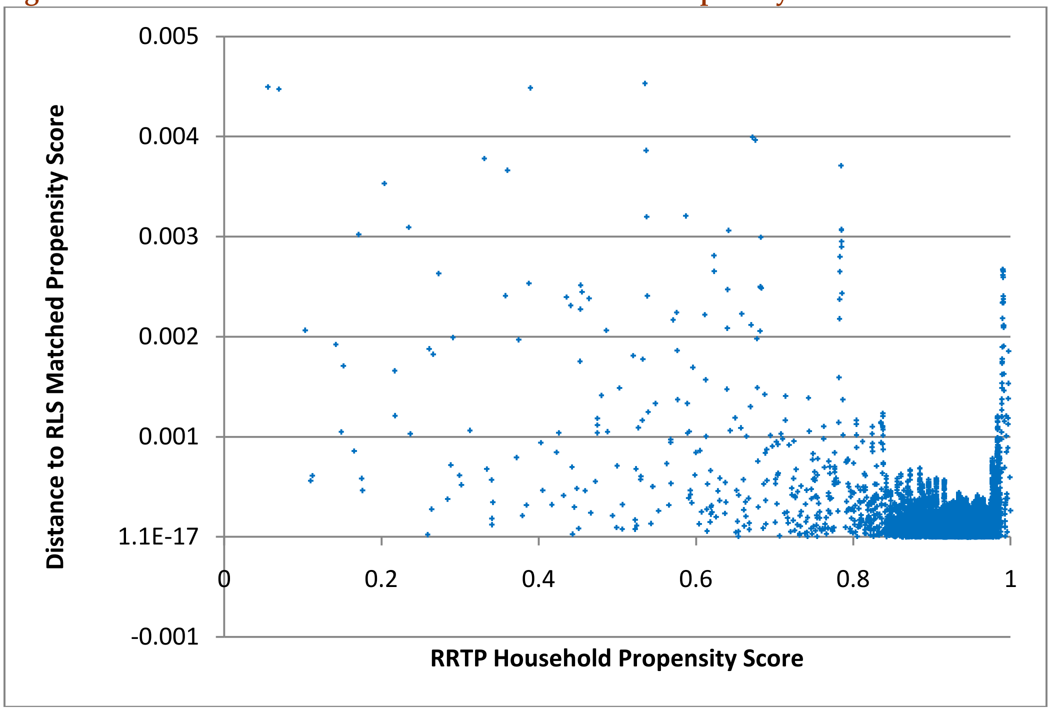
Source: Navigant analysis

Figure 14. Distribution of Propensity Scores > 0.8.



Source: Navigant analysis

Figure 15. Distance between RRTP and Matched RLS Propensity Scores



Source: Navigant analysis

Table 11. Propensity Score Summary Statistics

Statistic	Value
Total number of households in the analysis:	
RRTP households	8151
RLS households	872
Average propensity score:	
Overall:	0.9033
RRTP households	0.9174
RSL households:	0.7717
Average difference in propensity score between RRTP household and its match:	0.000179
RLS multiple-match statistics:	
Number of households without a match:	154
Average number of matches per RLS household, conditional on at least one match:	11.37
Median number of matches per RLS household	6
Maximum number of matches per RLS household	75

Source: Navigant analysis

3.2.5 Estimating Hourly Demand Impacts using Regression Analysis

With the set of control households in hand, it is possible to use regression analysis to estimate, for every hour of every season in the program period, and for each of two day types (weekdays vs. weekends), hourly electricity consumption by RRTP households and their matched control households, thereby providing the basis for calculating the effect of the RRTP program on average hourly energy consumption. So, for instance, developing load curves for summer 2007 weekdays requires the estimation of 24 regression equations, one for each hour of the day. In the discussion below, the time subscript *"t"* pertains to the t^{th} day of the season, because the hour is the same for every observation in the particular regression –there is a regression for the hour ending at 1 AM, the hour ending at 2 AM, etc.

To assure proper identification of the effect of the RRTP program on electricity consumption, the variables used in each hourly regression must account for several key factors influencing consumption:

- $Temp_t$: temperature for the hour on day t;
- $Preconsumption_k$: the average consumption of household *k* in the pre-program year (2006);
- $RRTP_k$: a 0/1 binary variable taking a value of 0 if household *k* is a control household, and 1 if it is an RRTP household;
- whether the hour is marked by one of several RRTP "events", as explained below;
- the type of RRTP household, as explained below.

The set of RRTP events that might influence the energy consumption behavior of at least some RRTP households are those discussed in the description of the RRTP program in section 2.2:

- DA_alert_t: a 0/1 binary variable taking a value of 1 if a day-ahead alert is in force in the specified hour on day t;
- $RT10\_alert_t$: a 0/1 binary variable taking a value of 1 if a real-time price alert with a threshold of 10 cents is in force in the specified hour on day t;
- $RT14\_alert_t$: a 0/1 binary variable taking a value of 1 if a real-time price alert with a threshold of 14 cents is in force in the specified hour on day t;
- $LG10_t$: a 0/1 binary variable taking a value of 1 if a Load Guard event with a threshold of 10 cents is in force in the specified hour on day t;
- $LG14_t$: a 0/1 binary variable taking a value of 1 if a Load Guard event with a threshold of 14 cents is in force in the specified hour on day t;
- $AC\_cycling_t$: a 0/1 binary variable taking a value of 1 if an AC-cycling program is in force in the specified hour on day t.

Possibly different RRTP households would react differently to these events; for instance, an RRTP household receiving RT-10 alerts possibly would behave differently in hours in which an RT-10 alert is in effect than would an RRTP household receiving only RT-14 alerts.[10] Moreover, it is possible

[10] Here as elsewhere in the report we use the following shorthand to denote RRTP alerts and subgroups:

- RT-10 alert: a real-time price alert at the 10-cent threshold;
- RT-14 alert: a real-time price alert at the 14-cent threshold;

that even on non-event days, households that chose to receive RT-10 alerts behave differently than those receiving RT-14 alerts, not least because RT-14 alerts is the default assignment for the RRTP program, and an RRTP household must request the receipt of RT-10 alerts, thereby signaling relatively high engagement in the program. With this in mind, the hourly regression analysis includes the following variables to identify differences among various subgroups of RRTP households in their electricity consumption behavior:

- $RT14\_HH_{kt}$: a 0/1 binary variable taking a value of 1 if household k is enrolled on day t to receive real-time alerts (via email or text message) at the 14-cent threshold. This is the default alert threshold;
- $RT10\_HH_{kt}$: a 0/1 binary variable taking a value of 1 if household k is enrolled on day t to receive real-time alerts (via email or text message) at the 10-cent threshold;
- $LG10\_HH_{kt}$: a 0/1 binary variable taking a value of 1 if household k is enrolled in Load Guard on day t, with events called at the 10-cent threshold;
- $LG14\_HH_{kt}$: a 0/1 binary variable taking a value of 1 if household k is enrolled in Load Guard on day t, with events called at the 14-cent threshold;

All of the variables listed above are used individually in the hourly regression equations, and many are used in interaction terms to identify differential responses by RRTP and control households to temperature and events. For instance, the interaction $RRTP_k \cdot Temp_t$ captures whether, and to what degree, RRTP and control households respond differently to temperature. As another example, $RT14\_HH_{kt} \cdot RT14\_alert_t$ captures the effect of RT-14 alerts on households receiving the alerts.

Formally, denoting by HEC_{kt} the electricity consumption by household k on day t for the hour of interest (e.g. 2 PM on weekdays, summer 2010), the hourly regression models take the following linear form:

- RT-10 household: an RRTP household enrolled to receive RT-10 alerts;
- RT-14 household: an RRTP household enrolled to receive RT-14 alerts;
- PA household: an RRTP household that does not receive any alerts via email or text messaging;
- DA alert: a day-ahead price alert;
- LG-10 event: a Load Guard event at the 10-cent threshold;
- LG-14 event a Load Guard event at the 14-cent threshold;
- LG-10 household: an RRTP household enrolled to respond to LG-10 events;
- LG-14 household: an RRTP household enrolled to respond to LG-14 events.

$$
\begin{aligned}
HEC_{kt} = {} & \alpha_0 + \alpha_1 RRTP_k + \alpha_2 Temp + \alpha_3 PreConsumption_k \\
& + \alpha_4 DA\_alert_t + \alpha_5 RT10\_alert_t + \alpha_6 RT14\_alert_t + \alpha_7 LG10_t + \alpha_8 LG14_t \\
& + \alpha_9 ACC\_50_t + \alpha_{10} ACC\_100_t \\
& + \alpha_{11} RRTP_k \cdot Temp_t + \alpha_{12} RRTP_k \cdot PreConsumption_k \\
& + \alpha_{13} RRTP_k \cdot DA\_alert_t + \alpha_{14} RRTP_k \cdot RT10\_alert_t + \alpha_{15} RRTP_k \cdot RT14\_alert_t \\
& + \alpha_{16} RRTP_k \cdot LG10_t + \alpha_{17} RRTP_k \cdot LG14_t \\
& + \alpha_{18} RT10\_HH_{kt} + \alpha_{19} RT14\_HH_{kt} + \alpha_{20} LG10\_HH_{kt} + \alpha_{21} LG14\_HH_{kt} \\
& + \alpha_{22} RT10\_HH_{kt} \cdot DA\_alert_t + \alpha_{23} RT10\_HH_{kt} \cdot RT10\_alert_t \\
& + \alpha_{24} RT14\_HH_{kt} \cdot DA\_alert_t + \alpha_{25} RT14\_HH_{kt} \cdot RT14\_alert_t \\
& + \alpha_{26} LG10\_HH_{kt} \cdot LG10_t + \alpha_{27} LG14\_HH_{kt} \cdot LG14_t + \varepsilon_{kt}
\end{aligned} \tag{3}
$$

This regression was run 48 times (24 hours for weekdays, 24 hours for weekends) for each of 15 seasons in the program period (4 seasons in each of the first three years, and 3 seasons in 2010; the data extends only until October 31 and so we did not conduct the analysis for fall 2010, which covers the period Sept 1-Dec 1), and so the total number of regression equations generated for the analysis is 720. All models were estimated using ordinary least squares (OLS regression). To give a general sense of the results, Table 50 in appendix A provides coefficient estimates and standard errors for the summer 2010 weekday hours of 2 AM, 8 AM, 2 PM, and 8 PM.

3.2.6 Applying the Coefficient Estimates from Hourly Regressions to Generate Load Curves

With the coefficient estimates from the hourly regressions in hand, estimating load curves for RRTP households with and without the RRTP program is straightforward. For instance, letting $\overline{Temp}^h$ denote the average temperature for the hour of interest, and letting $\overline{Preconsumption}^h$ denote the average preconsumption of RRTP households for that hour, for days where the hour experiences no events the predicted average consumption in the absence of the RRTP program (the baseline condition) is simply,

$$\overline{HEC}^h_{baseline} = \hat{\alpha}_0 + \hat{\alpha}_2 \overline{Temp}^h + \hat{\alpha}_3 \overline{PreConsumption}^h , \tag{4}$$

where "^" indicates the estimated value of the parameter. By contrast, under the same conditions average consumption by households enrolled in the RRTP program and which receive RT-10 alerts, but are not enrolled in Load Guard, is:

$$\overline{HEC}^h_{RRTP} = \hat{\alpha}_0 + \hat{\alpha}_1 + \left(\hat{\alpha}_2 + \hat{\alpha}_{11}\right) \cdot \overline{Temp}^h + \left(\hat{\alpha}_3 + \hat{\alpha}_{12}\right) \cdot \overline{PreConsumption}^h + \hat{\alpha}_{18} . \tag{5}$$

Subtracting (4) from (5) generates the estimated average energy savings for the hour for RRTP households enrolled in the RT-10 program:

$$Savings^h = \overline{HEC}^h_{baseline} - \overline{HEC}^h_{RRTP} = -\left(\hat{\alpha}_1 + \hat{\alpha}_{18} + \hat{\alpha}_{11} \cdot \overline{Temp}^h + \hat{\alpha}_{12} \cdot \overline{PreConsumption}^h\right). \tag{6}$$

Similar calculations can be made to generate average consumption and energy savings at each hour of the day to develop load shapes and savings for various RRTP subgroups, and to determine the effects of various event types (no event, RT-10 event, RT-14 and LG-10 event, etc.).

It is impractical to report all combinations of results –the impact of the program on the various types of RRTP households under various event conditions (no event, RT-10 alert, RT-10 alert with LG-10 event, etc.). Instead we attempt to develop a broad understanding of the impact of the RRTP program on hourly load curves by focusing on load curves and/or event impacts for the following combinations of sub-groups and event days:

- RT-14 households, non-event days. RT-14 households are the most common RRTP subgroup (6,021 households in August 2010, see Figure 4 in section 2.3.1 on page 14), and the vast majority of hours are non-event hours.
- PA households, non-event days. As shown in Figure 4, PA households are the second most common RRTP household.
- RT-10 households, non-event days. Although RT-10 households typically compose no more than 7% of RRTP households, their decision to receive RT-10 alerts indicates a relatively high level of program engagement.
- RT-14 households, RT-14 event days.
- RT-10 households, RT-10 event days.
- Load Guard-10 households, Load Guard-10 event days.
- Load Guard-14 households, Load Guard-14 event days.

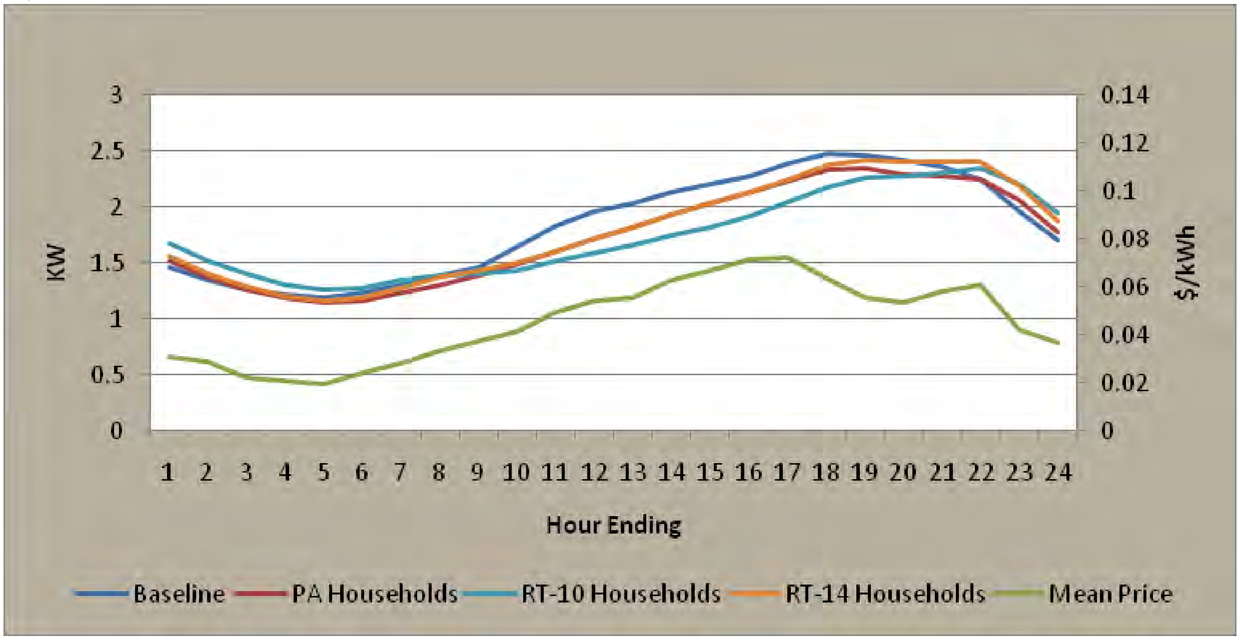
3.2.7 Summer Hourly Load Shapes, Non-event days

Figure 16-Figure 19 present hourly mean prices and average load shapes for RT-14, PA, and RT-10 households for the program summers 2007-2010, weekdays, non-event days. The following general impacts are indicated by the figures:

1. For all three RRTP types, households shift their energy consumption away from the high-priced afternoon hours to the low-priced overnight hours.
2. Consumption is greatest in 2010, the hottest summer of the 4-year program period.
3. The hourly consumption behavior of RT-14 and PA households is very similar. This is not surprising in light of the fact that RT-14 is the default threshold for alerts, and so the only observable difference between RT-14 and PA households is that the latter either did not provide an email address, or (in the case of a small minority) requested no email or text alerts.
4. RT-10 households appear to undertake greater shifting of energy consumption across hours than do RT-14 and PA households. This is consistent with their decision to receive RT-10 alerts.

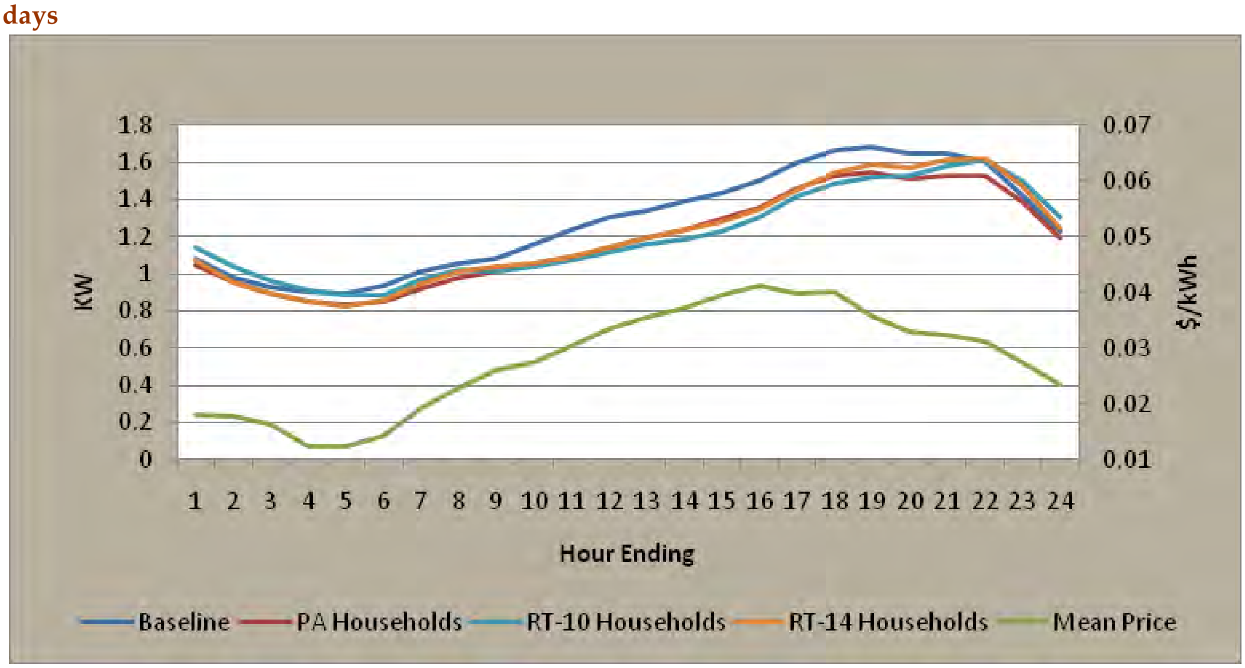
The load curves in Figure 16-Figure 19 apply to the *average* temperatures for each hour in each summer. We found that although an increase in temperatures has a significant effect on load curves, it tends to raise the baseline and RRTP customer load curves by very similar amounts, so that its effect on program savings is small. For instance, on a summer 2010 weekday a 10F increase in the temperature at 4 PM increases baseline kW consumption by 0.712 kW, and increases the kW consumption of RRTP households by 0.707, for an increase in program savings of 0.005 kW.

Figure 16. Hourly Load Shapes and Hourly Mean Price, Summer 2010, Weekdays, Non-event days



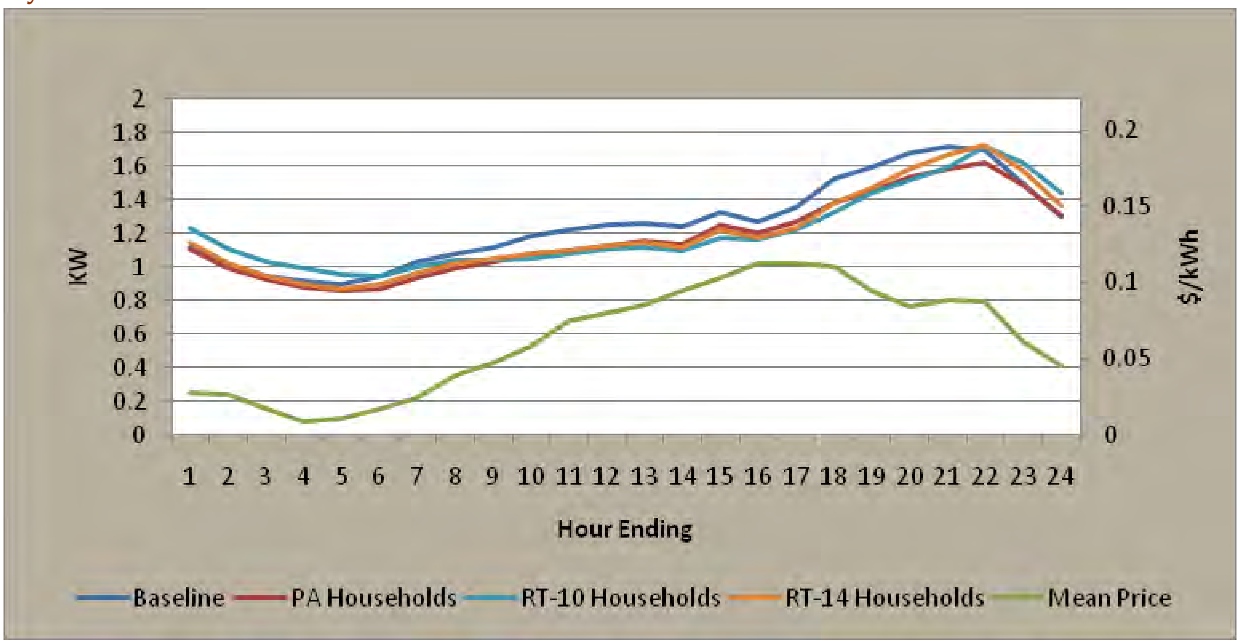
Source: Navigant analysis

Figure 17. Hourly Load Shapes and Hourly Mean Price, Summer 2009, Weekdays, Non-event days



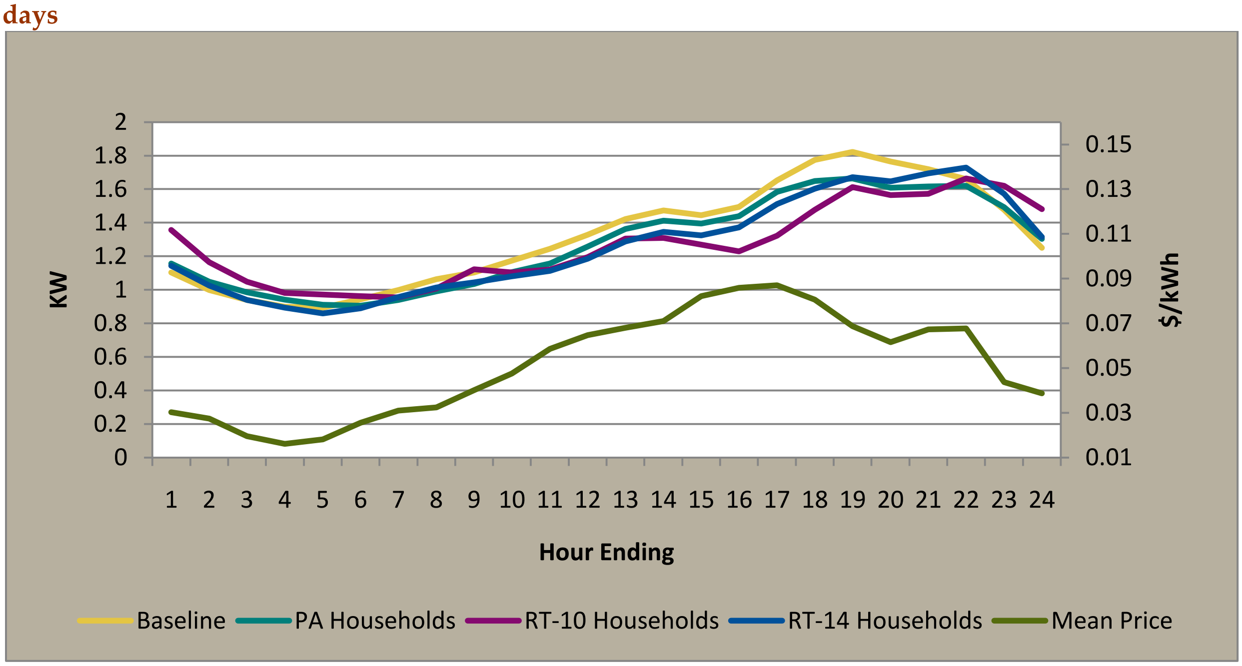
Source: Navigant analysis

Figure 18. Hourly Load Shapes and Hourly Mean Price, Summer 2008, Weekdays, Non-event days



Source: Navigant analysis

Figure 19. Hourly Load Shapes and Hourly Mean Price, Summer 2007, Weekdays, Non-event days



Source: Navigant analysis

Figure 20 demonstrates the responsiveness of RRTP households to prices, by graphing the average change from baseline in hourly energy consumption, and the mean hourly price for summer 2010 weekdays. This relationship foreshadows the discussion of the price elasticity of demand presented in section 3.3 on page 55.

Figure 20. Hourly Mean Price and Mean Change from Baseline Hourly Energy Consumption by RRTP Households, Summer Weekdays 2010.

Source: Navigant analysis

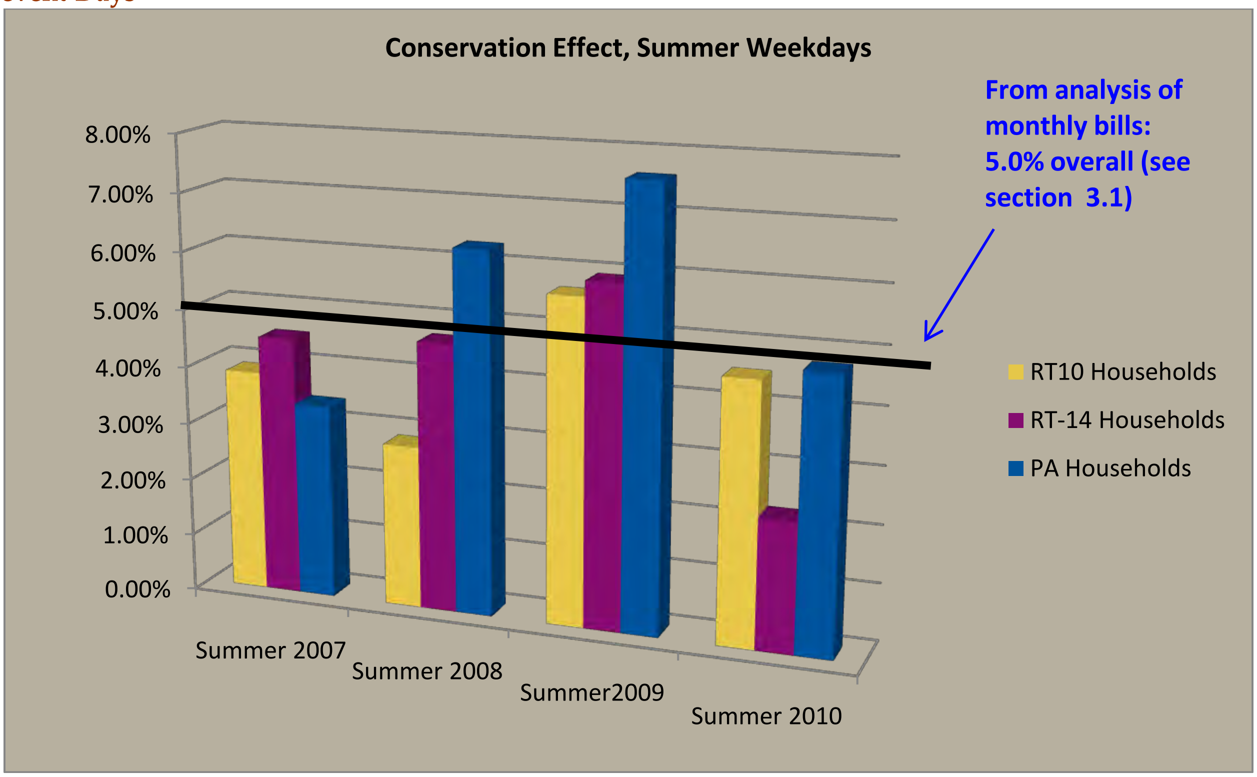
Figure 21 presents the conservation effects for summer weekdays, non-event days, for the three RRTP subgroups examined here. The conservation effect on non-event days is, on average, similar to that predicted by the monthly billing analysis described in the previous section (section 3.1 on page 22).[11] Interestingly, PA households appear to conserve the highest percentage of energy; possibly this reflects a passive response to the program, such as increasing thermostat settings for afternoon hours of summer weekdays and not reducing the setting when energy prices fall. Conservation was highest in 2009, which was a very cool summer and so conservation came at relatively low cost in terms of comfort.

The load curves for weekends are typified by those shown for summer 2010 in Figure 22. Generally the same pattern of consumption-shifting behavior observed on weekdays persists on weekends, but the shifting is generally less pronounced. The behavioral comparison across the three RRTP groups also persists: RT-10 households appear to generate the greatest consumption-shifting, and PA and RT-14 households exhibit similar consumption behavior. Consumption is noticeably higher in the

[11] The conservation effect is not exactly the same due to the fact that Figure 20 is restricted to subsets of RRTP households on a subset of days, and also perhaps due to differences in the data used to estimate the effect.

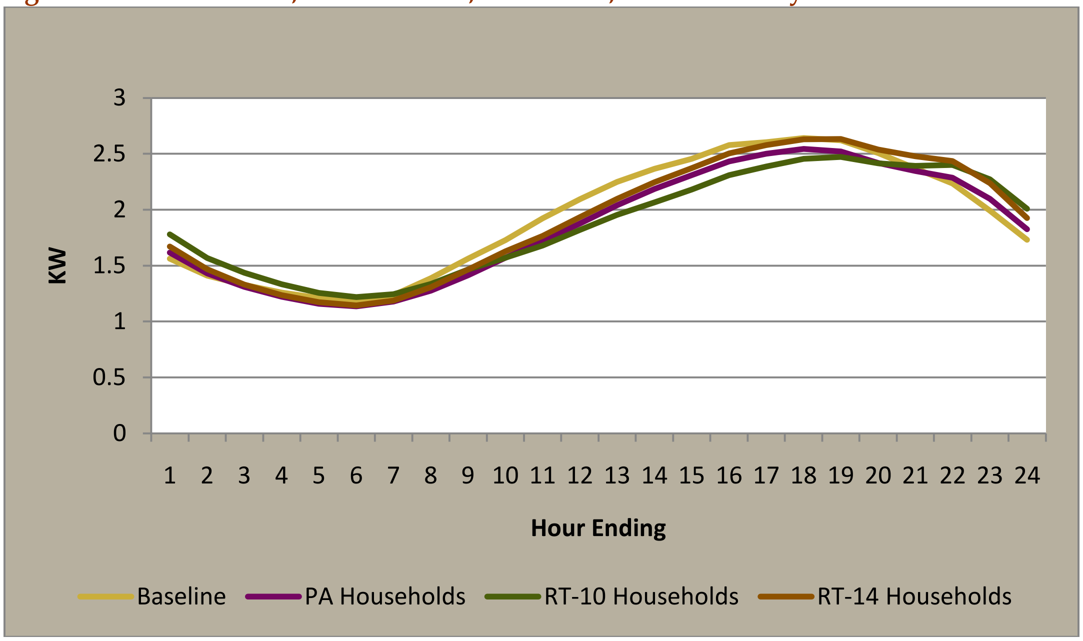
hot summer of 2010 than in the previous summers. Overall conservation effects are also similar to those observed on weekdays.

Figure 21. Summer 2007-2010 Conservation Effects, by RRTP household types, Weekdays, Non-event Days



Source: Navigant analysis

Figure 22. Load Curves, Summer 2010, Weekends, Non-event days



Source: Navigant analysis

3.2.8 Summer Impacts of Day-Ahead Price Alerts

As shown in Figure 11 on page 20, the large majority of DA-alerts took place in the summers of 2007 and 2008. Here we focus on the summer of 2008 because of the larger number of RRTP households. In the summer of 2008 the DA-alerts were limited to the hours of 11 AM-8 PM, but here we limit the analysis to those hours with at least 5 DA-alerts, 1 PM-6 PM.[12]

Figure 23 presents the estimated effects of the alerts on consumption by PA households in 2008; this is the effect above and beyond the effect of the RRTP program overall, and is captured by the coefficient on the term $RRTP_k \cdot DA\_alert_t$ in equation (3). To provide perspective of the effect, Figure 24 shows baseline consumption, consumption by PA households in the absence of a DA alert, and consumption by PA households in the presence of an alert, for the four hours for which the effect is statistically significant (2 PM -5 PM).

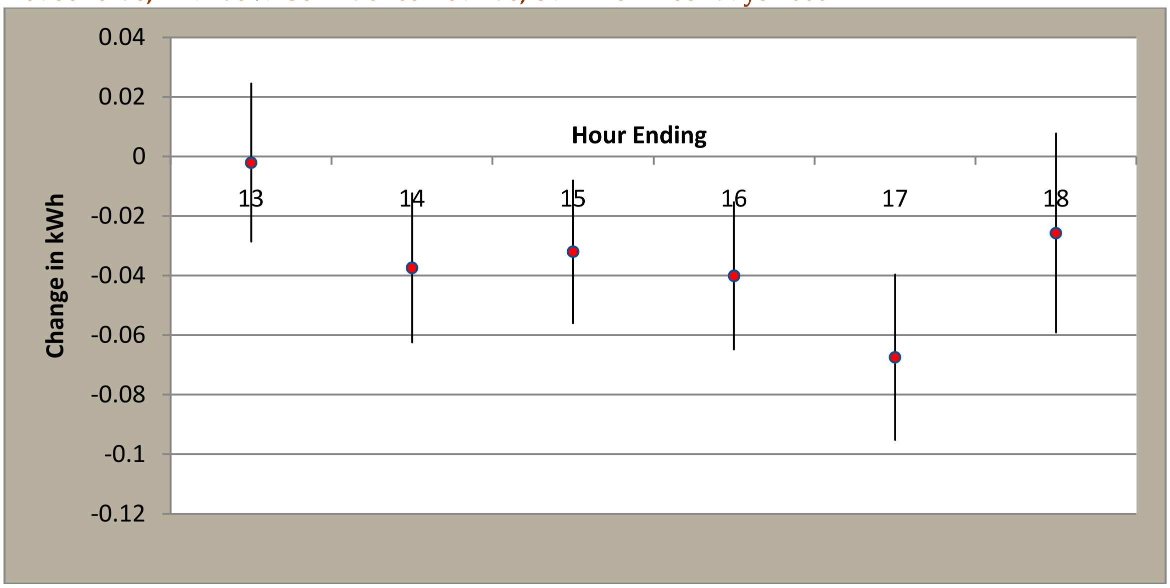
Overall, regression results indicate the following:

1. In 2008, DA-alerts had at best a slight average hourly effect on household energy saving. For PA households, savings were in the range of 0.0-0.04 kW; for RT-10 households savings were in the range of 0.0 to 0.07; and for RT-14 households savings were, inexplicably, in the negative range of -0.0 to -0.07.

[12] In this discussion as throughout this report, hours refer to “hours ending”. So, for instance, the statement “from 1 PM to 2 PM” refers to the two hours ending at 1 PM and 2 PM.

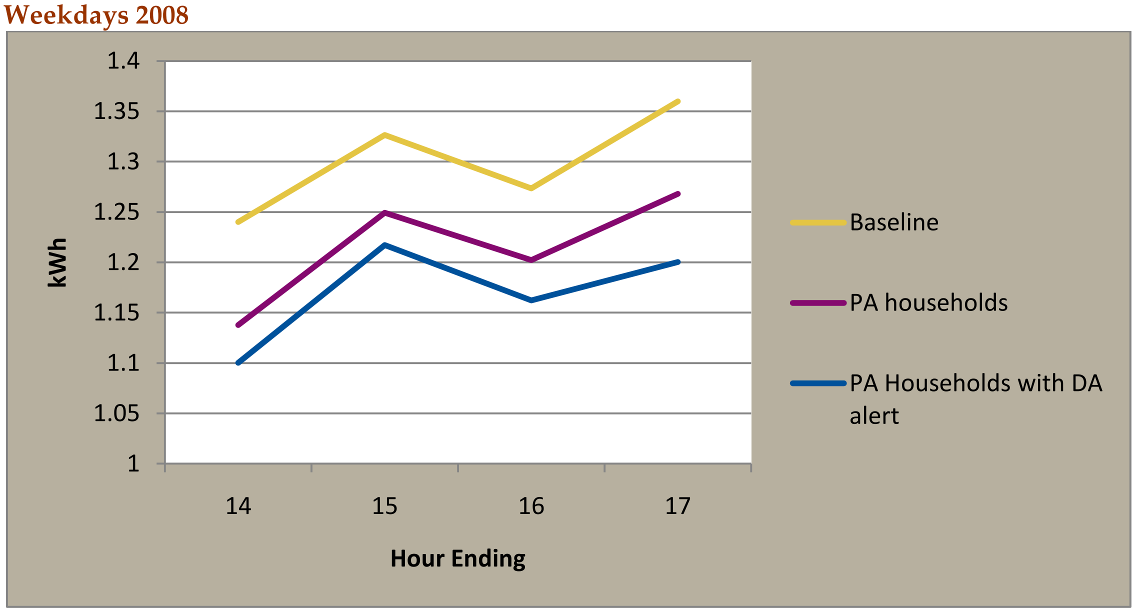
2. Enrollment in the RRTP program has changed dramatically over the past 2 years, and so, given that there have been no DA-alerts for several years, the current impact of DA alerts is unclear.

Figure 23. Estimated Direct Effect of Day-Ahead Price Alerts on Energy Consumption by PA Households, with 95% Confidence Bounds, Summer Weekdays 2008



[a]If confidence bounds cross the 0-axis the estimated effect is not statistically significant at the .05 level; analysis limited to hours with at least 5 day-ahead alerts). *Source: Navigant analysis*

Figure 24. Effect of Day-Ahead Price Alert on Energy Consumption by PA Households, Summer Weekdays 2008



Source: Navigant analysis

3.2.9 Summer Impacts of Real-Time Price Alerts

Summer real-time price alerts were called primarily in 2008 and 2010 (see Figure 11 on page 20), and so the analysis here focuses on these summers. Moreover, we consider only those hours with at least 5 alerts. To summarize:

- In summer 2008 there were 164 RT-10 alerts spread across 76 days, covering the hours of 8 AM-2 AM.[13] The hours with at least 5 alerts extended from 10AM-11PM.
- In summer 2008 there were 72 RT-14 alerts spread across 42 days, covering the hours of 8 AM-12 AM. The hours with at least 5 alerts extended from 11AM-9PM.
- In summer 2010 there were 38 RT-10 alerts spread across 28 days, covering the hours of 8 AM-12 AM. The hours with at least 5 alerts extended from 3 PM to 11 PM.
- In summer 2010 there were 17 RT-14 alerts spread across 13 days, covering the hours of 8 AM-12 AM. The hours with at least 5 alerts extended from 3 PM to 6 PM.

The direct effect of alerts is revealed by the interaction terms $RT10\_HH_{kt} \cdot RT10\_alert_t$ and $RT14\_HH_{kt} \cdot RT14\_alert_t$ in equation (3), which indicate the response of households receiving the alerts via email or text message.

An important caveat is that real time alerts typically lasted for 4 hours, and so an alert might engender a "snapback" effect towards the end of its run. So, for instance, the savings response to an alert starting at 2 PM might be strong for the first two hours, but wane by 5 PM. This behavior would be reflected by weaker or even negative estimated savings for the evening hours when many alerts ended.

Figure 25 presents the direct effects of RT-10 alerts on consumption by RT-10 households during summer 2008. The direct effect of alerts is revealed by the interaction term $RT10\_HH_{kt} \cdot RT10\_alert_t$. The savings effect is generally small and statistically significant or nearly so only during the hours ending 2 PM-7PM. To provide perspective of the effect, Figure 26 shows baseline consumption, consumption by RT-10 households in the absence of an alert, and consumption by RT-10 households in the presence of an alert, for this interval (2 PM -7 PM). As with DA alerts, it is clear that the alerts provide a relatively small bump in the general program effect.

Figure 27 presents the direct effects of RT-14 alerts on consumption by RT-14 households during summer 2008. Generally effects are not statistically significant except for a very weak *negative* effect on savings in the evening hours –possibly a snapback effect as suggested above. Figure 28 provides perspective by showing baseline consumption, consumption by RT-14 households in the absence of an alert, and consumption by RT-14 households in the presence of an alert, for the full interval examined.

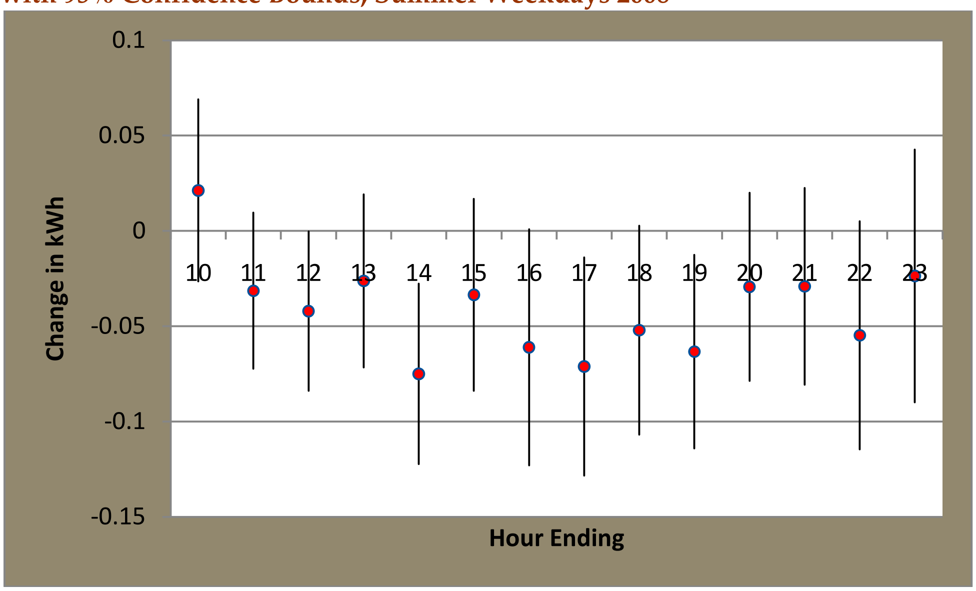
For both RT-10 alerts and RT-14 alerts in 2010, regression results indicate that the effect of the alerts for hours with at least 5 events was generally weak. RT-10 alerts generated statistically significant

[13] All times refer to full hours ending at the specified hour.

direct savings by RT-10 households **only** at 3 PM and 4 PM. As with summer 2008, the effects were small (0.087 kW at 3 PM, 0.043 kW at 4 PM). There were at least five events for RT-14 alerts only for the period 3PM to 6 PM, and savings were statistically significant but small and *negative* from 4 PM to 6 PM (negative savings ranging from 0.04 to 0.07).

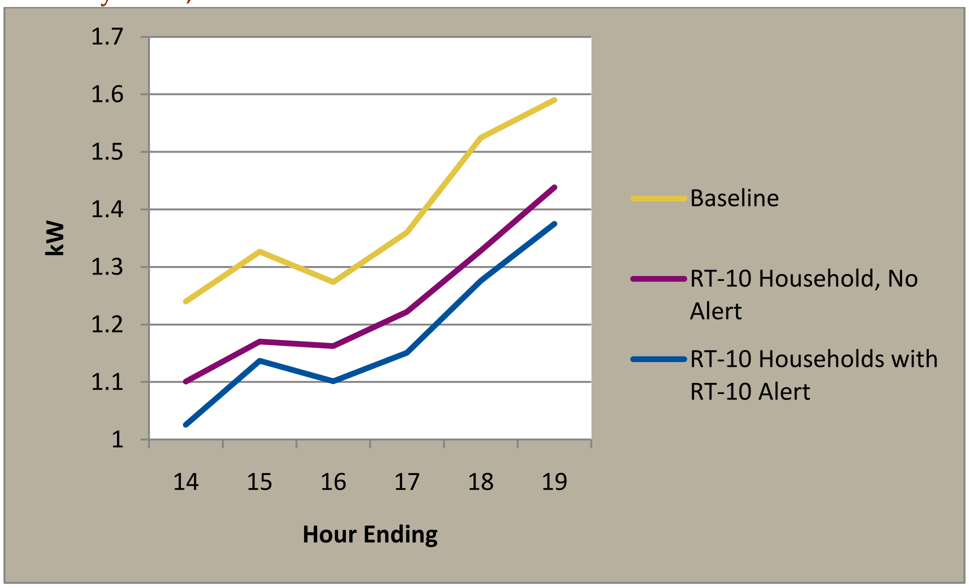
The overall conclusion of the analysis is that RT-10 alerts generate small hourly savings, on the order of 0.0-0.08 kW, during mid afternoon to early evening hours. There is no good statistical evidence that the alerts generate savings outside of these hours. There is no evidence that RT-14 alerts generate savings. That RT-10 alerts generate small saving, whereas RT-14 alerts appear to generate no savings, is likely due to the greater degree of engagement by RT-10 households.

Figure 25. Estimated Direct Effect of RT-10 Alerts on Energy Consumption by RT-10 Households, with 95% Confidence Bounds, Summer Weekdays 2008[a]



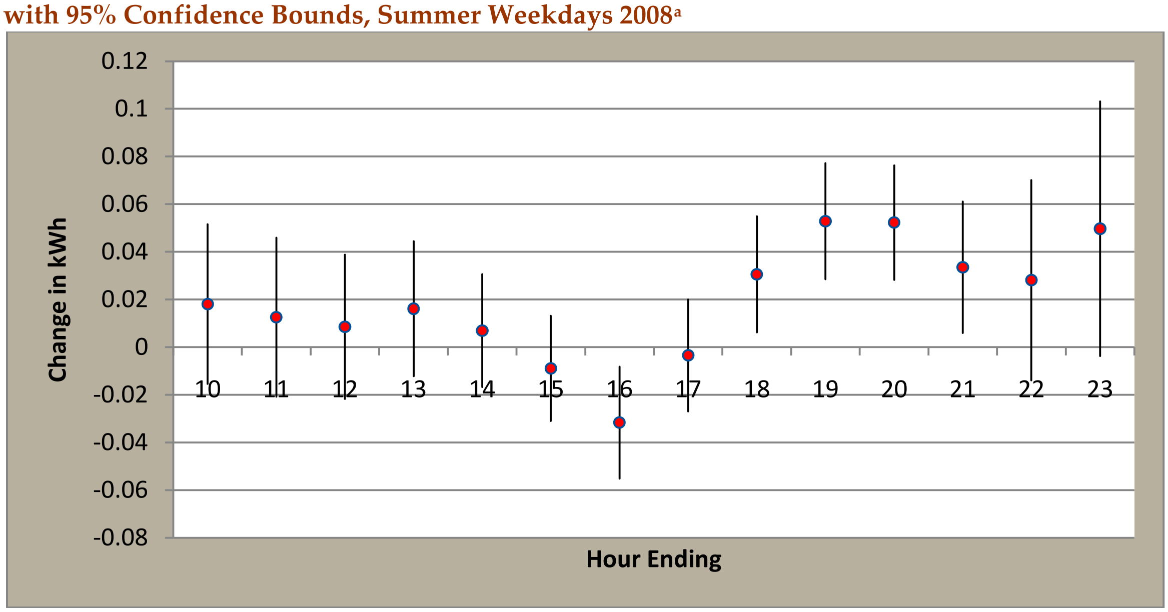
[a]If confidence bounds cross the 0-axis the estimated effect is not statistically significant at the .05 level; analysis limited to hours with at least 5 RT-10 alerts) . *Source: Navigant analysis*

Figure 26. Effect of RT-10 Alert on Energy Consumption by RT10 Households, Summer Weekdays 2008, 2PM-7PM



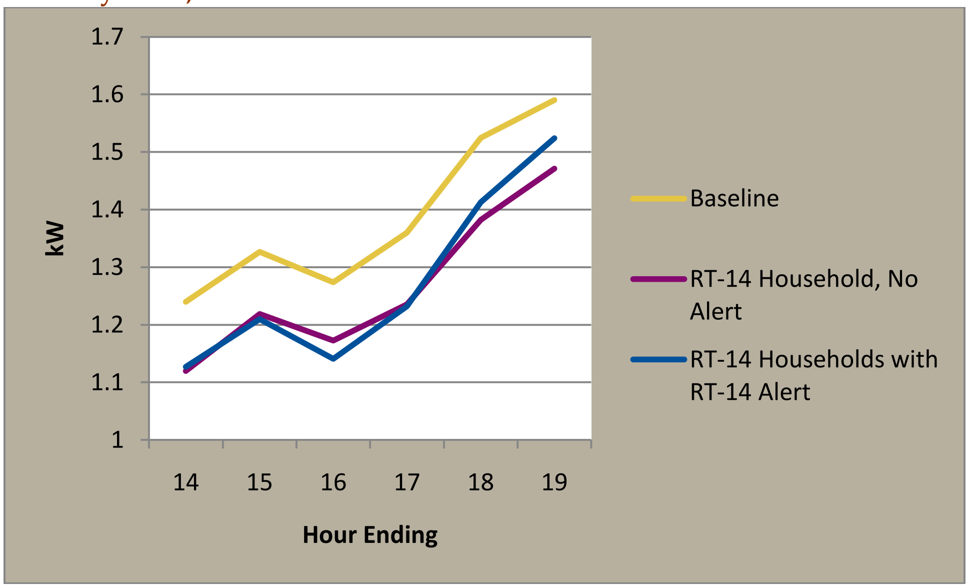
Source: Navigant analysis

Figure 27. Estimated Direct Effect of RT14 Alerts on Energy Consumption by RT14 Households, with 95% Confidence Bounds, Summer Weekdays 2008[a]



[a]If confidence bounds cross the 0-axis the estimated effect is not statistically significant at the .05 level; analysis limited to hours with at least 5 RT-14 alerts) *Source: Navigant analysis*

Figure 28. Effect of RT14 Alert on Energy Consumption by RT14 Households, Summer Weekdays 2008, 2PM-7PM



Source: Navigant analysis

3.2.10 Summer Impacts of Load Guard Events

Figure 11 on page 20 presents the number of Load Guard events in each year of the program. In light of the event history, we focus the current analysis of the program on weekdays during the summers of 2008 and 2010.

Impacts at the 10-cent threshold

In summer 2008 there were 76 days with Load Guard events at the 10-cent threshold; there were at least 5 events in every weekday hour from 9 AM to 12 AM. In summer 2010 there were 41 days with Load Guard events at the 10-cent threshold, with at least 5 events in every weekday hour from 11 AM to 6 PM, and 10 to 11 PM. The analysis is limited to these hours.

Figure 29-Figure 30 present the direct effects of LG-10 events on LG-10 households on summer weekdays in 2008 and 2010, respectively. This direct effect is captured by the interaction terms $LG10\_HH_{kt} \cdot LG10_t$ in equation (3). Figure 31-Figure 32 show the incremental direct effect of an LG-10 event on an event day in 2008 and 2010; the effect is presented for RT10 households enrolled in the LG-10 program. The figures show baseline consumption, consumption by LG10+ RT10 households in the absence of an event, and consumption by these households in the presence of an alert, for the relevant hourly intervals in each year (that is, those hours with at least 5 events). In general the average reduction in consumption from baseline by LG10+ RT10 households on event days is about 0.3 kW in mid-afternoon hours in 2008, and 0.8 kW in mid-afternoon hours in 2010. The difference in energy savings across years is likely due to in part to the change in the composition of the households in the RRTP program, and in part to the much hotter summer in 2010. The relatively

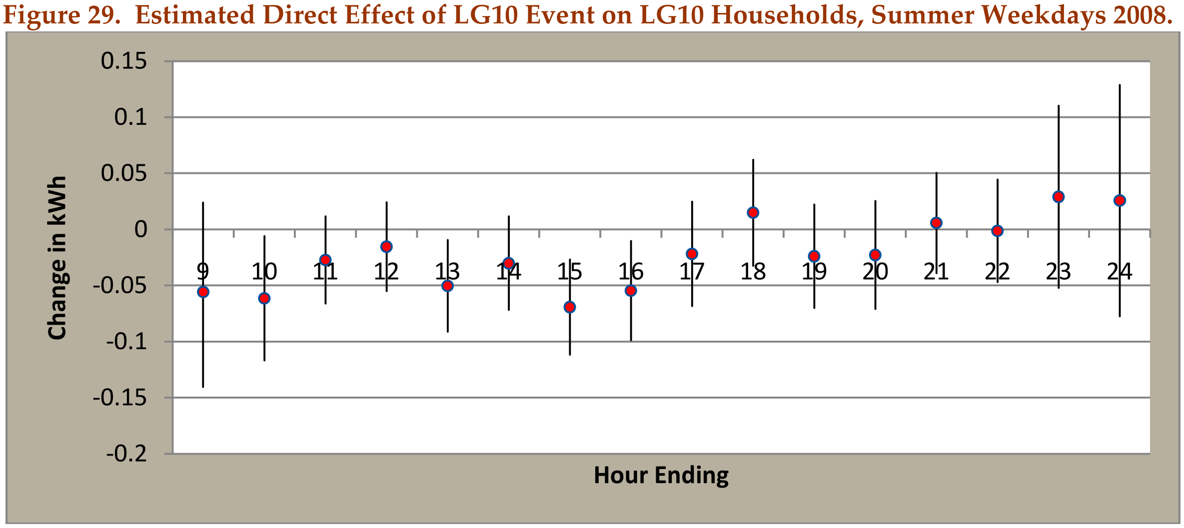
small portion of this savings directly attributable to the LG-10 program as compared to what is frequently found for DLC programs is due to the fact that households enrolled in the RRTP program are already making substantial efforts to shift their energy consumption to off-peak hours.

Impacts at the 14-cent threshold

In summer 2008 there were 42 days with Load Guard events at the 14-cent threshold; there were at least 5 events in every weekday hour from 11 AM to 10 PM. In summer 2010 there were 13 days with Load Guard events at the 14-cent threshold, with at least 5 events in the weekday hours ending at 4 PM and 5 PM. Generally the direct effect of LG-14 events on summer weekdays in 2008, as captured by the interaction term $LG14\_HH_{kt} \cdot LG14_t$ in equation (3) was both practically and statistically nonsignificant. In summer 2010 the direct effect on weekdays was -0.1651 kW for the hour ending at 4 PM, and -0.1719 for the hour ending at 5 PM, with both results statistically significant at the 0.01 level.

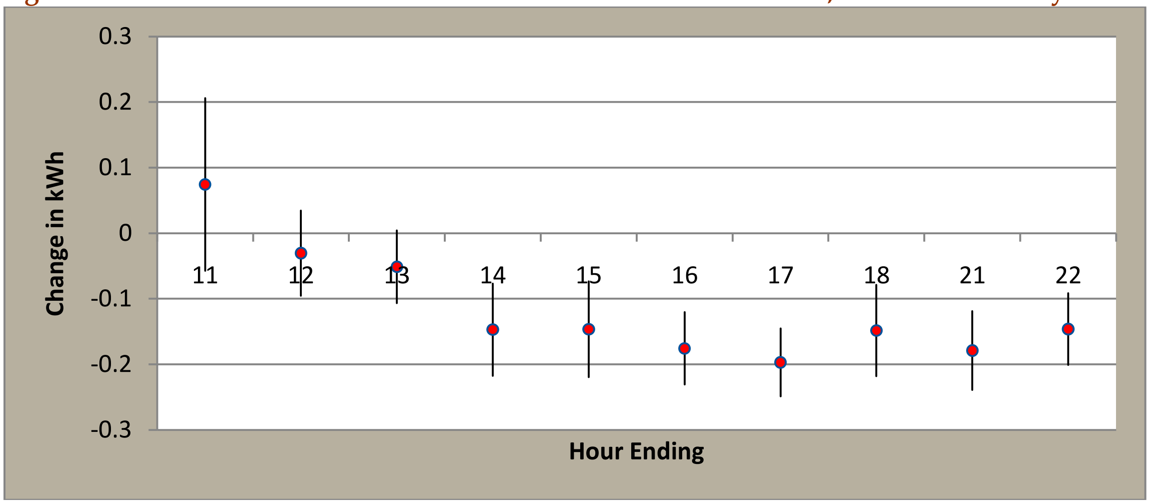
In summary, the Load Guard program at the 10-cent threshold has a statistically significant effect on summer weekday energy savings. The direct effect is considerably weaker than usually found for DLC programs because RRTP customers have already shifted energy consumption away from peak-demand hours.

Figure 29. Estimated Direct Effect of LG10 Event on LG10 Households, Summer Weekdays 2008.



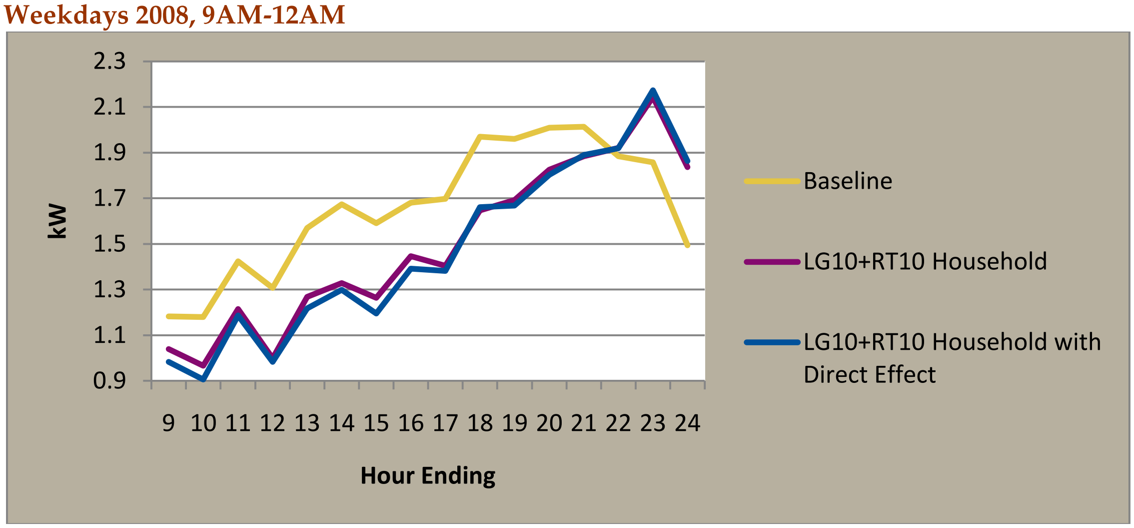
[a]If confidence bounds cross the 0-axis the estimated effect is not statistically significant at the .05 level; analysis limited to hours with at least 5 LG10 events). *Source: Navigant analysis*

Figure 30. Estimated Direct Effect of LG10 Event on LG Households, Summer Weekdays 2010.



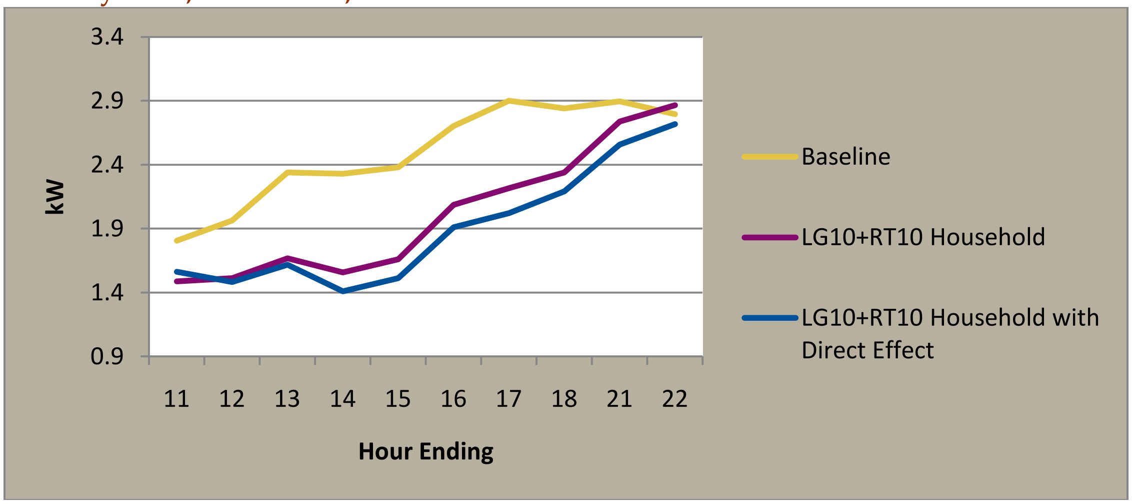
[a]If confidence bounds cross the 0-axis the estimated effect is not statistically significant at the .05 level; analysis limited to hours with at least 5 LG10 events) *Source: Navigant analysis*

Figure 31. Effect of LG10 Event on Energy Consumption by LG10+RT10 Households, Summer Weekdays 2008, 9AM-12AM



Source: Navigant analysis

Figure 32. Effect of LG10 Event on Energy Consumption by LG10+RT10 Households, Summer Weekdays 2010, 11AM-6 PM, 9 PM-10PM



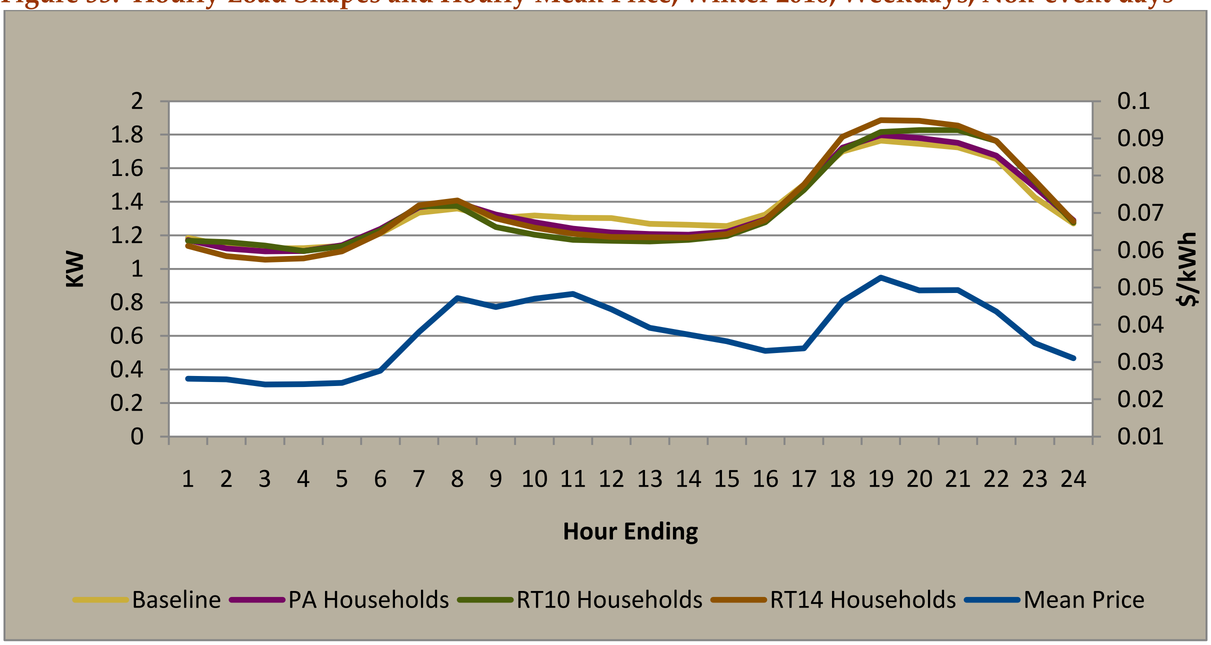
Source: Navigant analysis

3.2.11 Winter Hourly Load Shapes

Figure 33-Figure 36 present hourly mean prices and load curves for RT-14, PA, and RT-10 households for the program winters 2007-2010, weekdays, non-event days.[14] Figure 37 graphs the hourly change from baseline in RRTP household energy consumption, and the hourly mean price, for Winter 2010 weekdays. The following general impacts are indicated by the figures and review of the load shapes for winter weekends (not shown):

- As found in section 3.1 there is an overall conservation effect in the winter;
- RRTP Households appear to respond to high late morning and early afternoon prices, especially in 2009 and 2010, as evidenced by the sharp negative change from baseline consumption shown in Figure 37. But this appears to be offset by a snapback effect in early-mid evening when prices are high.

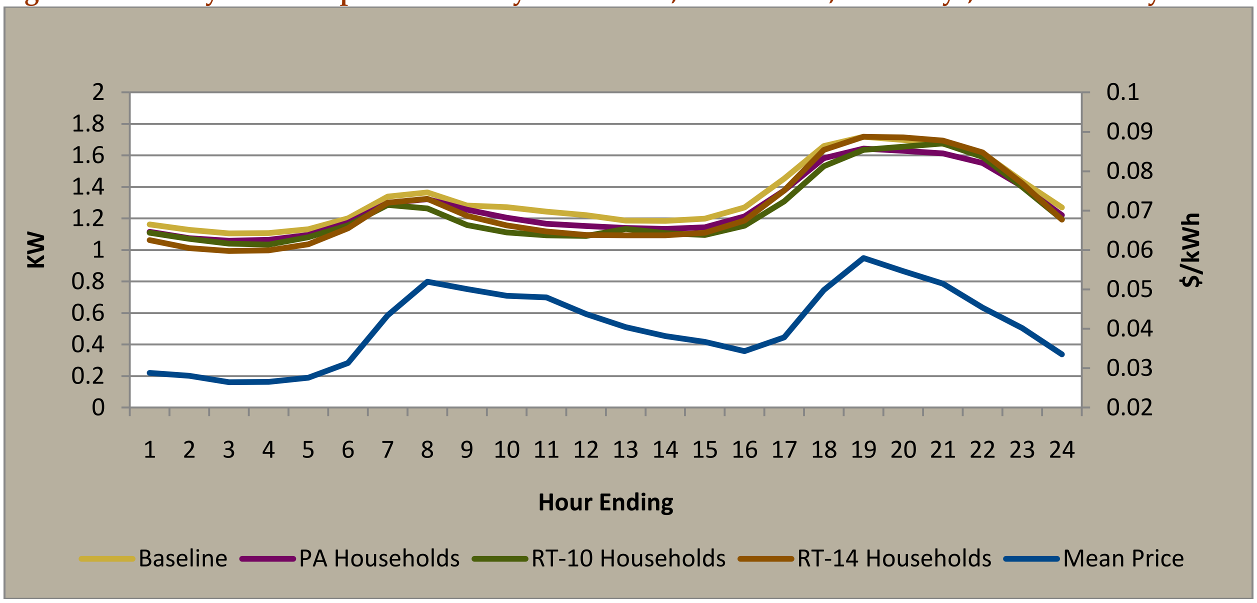
Figure 33. Hourly Load Shapes and Hourly Mean Price, Winter 2010, Weekdays, Non-event days



Source: Navigant analysis

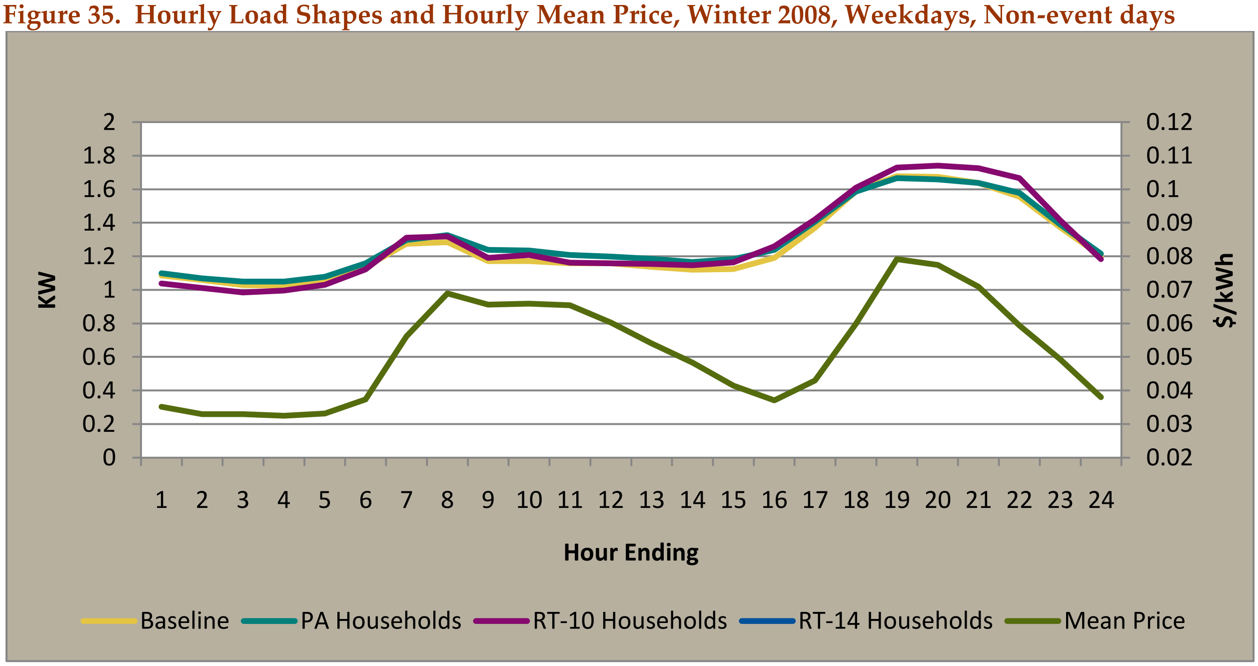
[14] Winter 2007 is restricted to the winter months January-February.

Figure 34. Hourly Load Shapes and Hourly Mean Price, Winter 2009, Weekdays, Non-event days



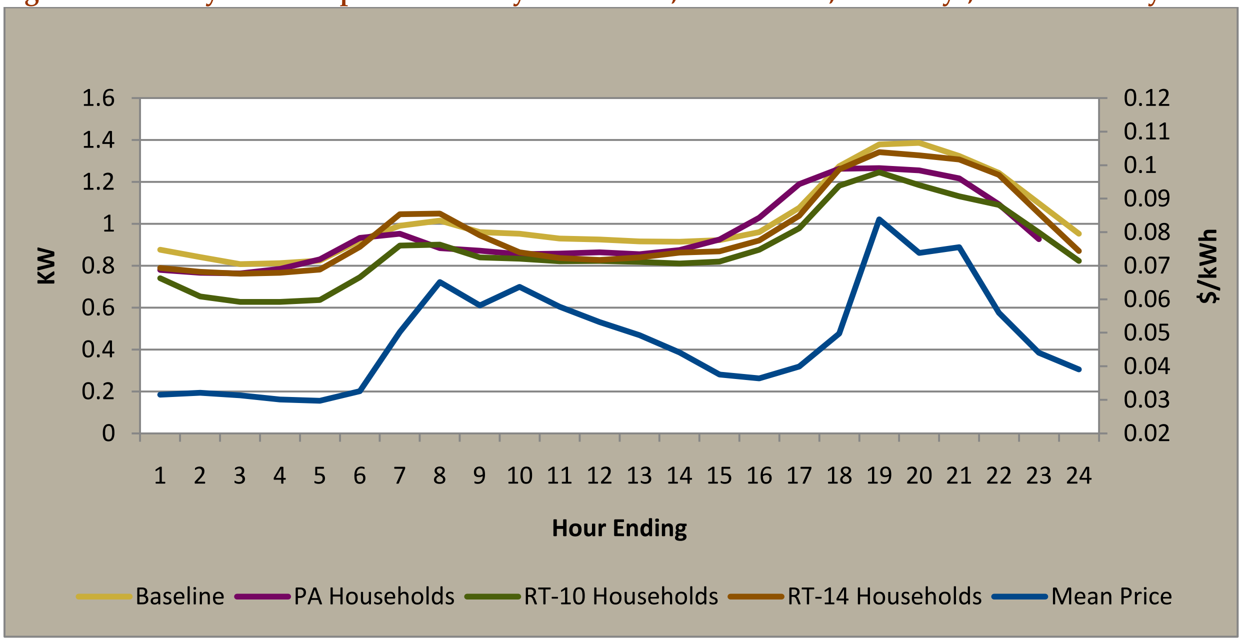
Source: Navigant analysis

Figure 35. Hourly Load Shapes and Hourly Mean Price, Winter 2008, Weekdays, Non-event days



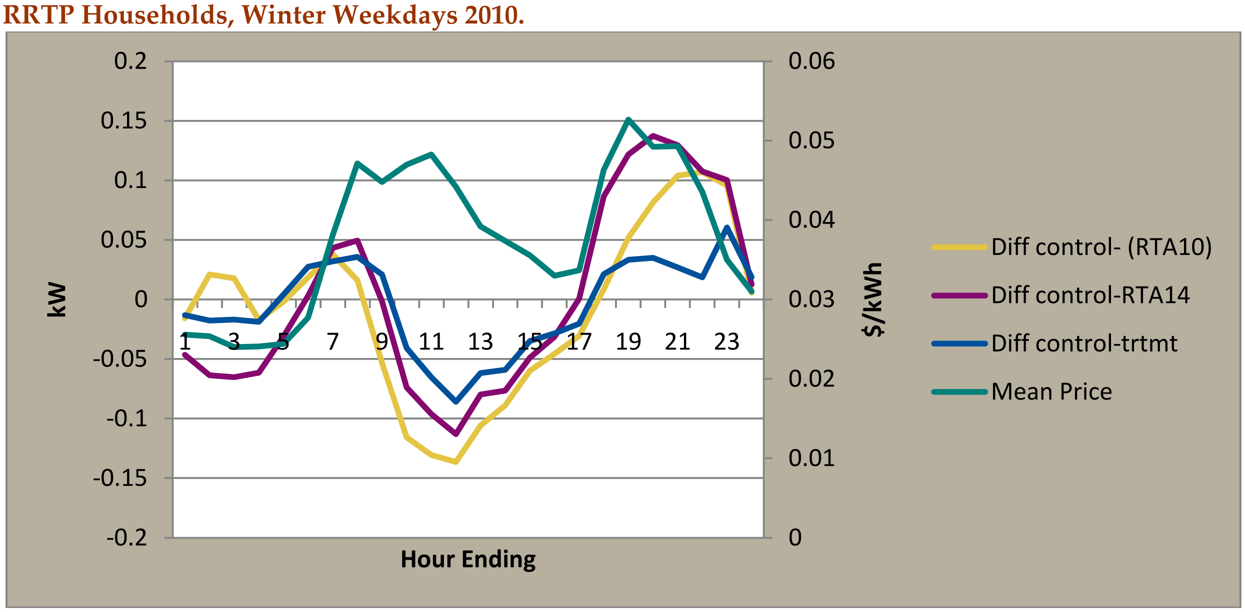
Source: Navigant analysis

Figure 36. Hourly Load Shapes and Hourly Mean Price, Winter 2007, Weekdays, Non-event days



Source: Navigant analysis

Figure 37. Hourly Mean Price and Mean Change from Baseline Hourly Energy Consumption by RRTP Households, Winter Weekdays 2010.

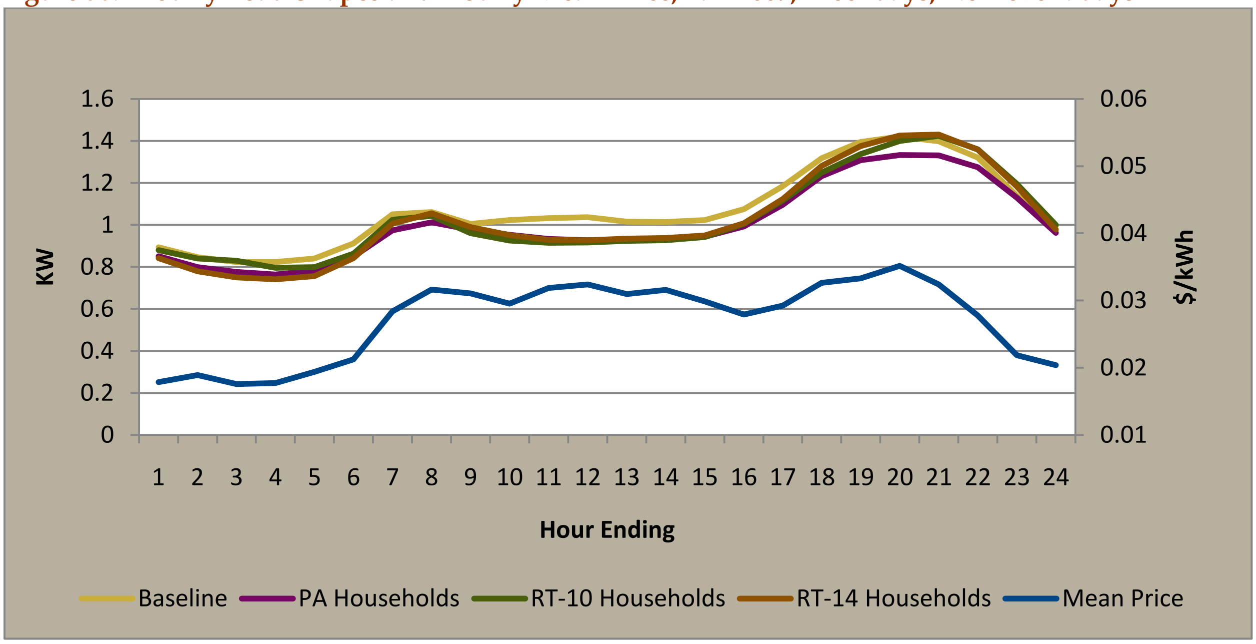


Source: Navigant analysis

3.2.12 Fall and Spring Hourly Load Shapes

Figure **38**-Figure 39 present hourly mean prices and load shapes for RT-14, PA, and RT-10 households for the fall 2009 and spring 2010, weekdays, non-event days.[15] There appears to be slight shifting away from high-priced hours in mid-morning to early afternoon, especially by RT-10 households in the spring. As in the winter, this is offset by snapback effects during early to mid evening, when prices are still fairly high.

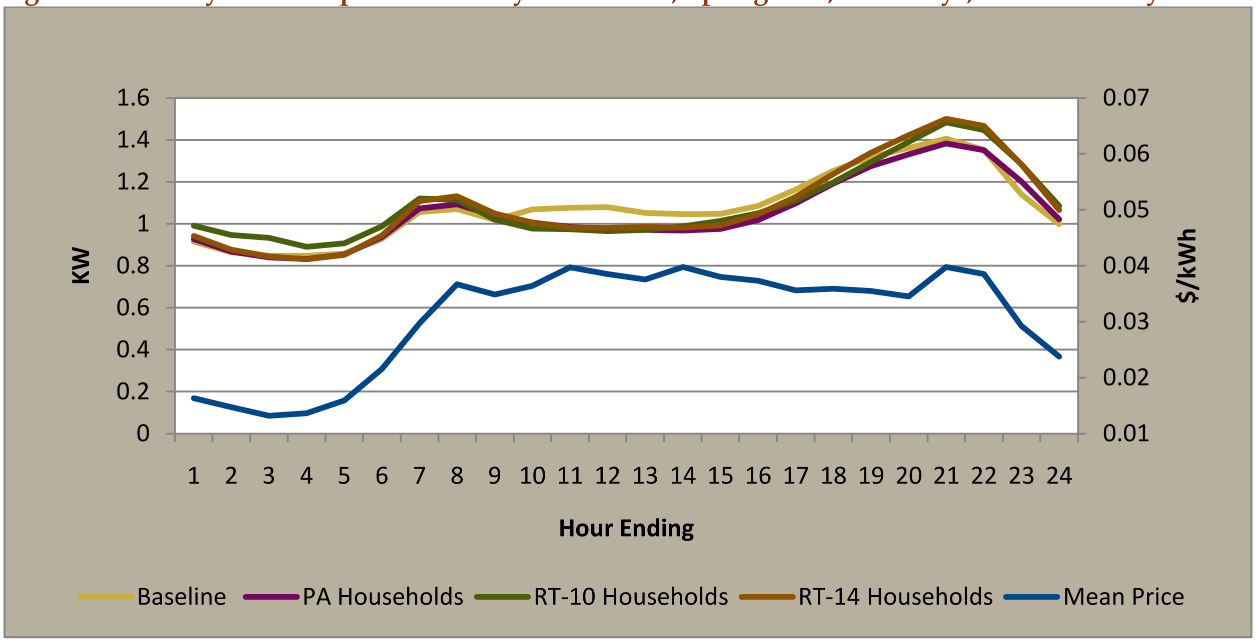
Figure 38. Hourly Load Shapes and Hourly Mean Price, Fall 2009, Weekdays, Non-event days



Source: Navigant analysis

[15] The analysis was started before the end of fall 2010, and so 2009 is the most recent year with a full season of data for fall.

Figure 39. Hourly Load Shapes and Hourly Mean Price, Spring 2010, Weekdays, Non-event days



Source: Navigant analysis

3.3 Price Responsiveness of RRTP Participants

The defining feature of the RRTP program is that households no longer face a fixed price for energy, but instead face real-time prices that change hourly. Consequently, observed behavioral changes in energy consumption—both the conservation effect estimated in section 3.1, and the shifting of load across hours revealed in section 3.2, are due to changes in prices. In the discussion here we focus on what the RRTP program reveals about household demand for energy, in particular the price responsiveness of households, as indicated by the price elasticity of demand. Such analysis provides insights to how future changes in the distribution of prices can be expected to affect the energy consumption behavior of RRTP households.

In general, RRTP households can be expected to respond to prices in a number of ways:

- **In the long run** they respond to the distribution of prices in their decisions concerning capital investments, such as energy efficient appliances. For instance, the opportunity to run appliances when prices are relatively low may reduce the incentive to buy an energy efficient appliance.
- **In the medium run** households respond to differences in *average hourly price* with a broad shift in energy consumption behavior as compared to their behavior under the fixed-price regime, forming new habits and modes of operation, such as running dishwashers at night. Such broad shifts in behavior are consistent with the information

provided to RRTP customers indicating that shifting energy consumption to overnight hours, when prices are low, reduces energy bills.

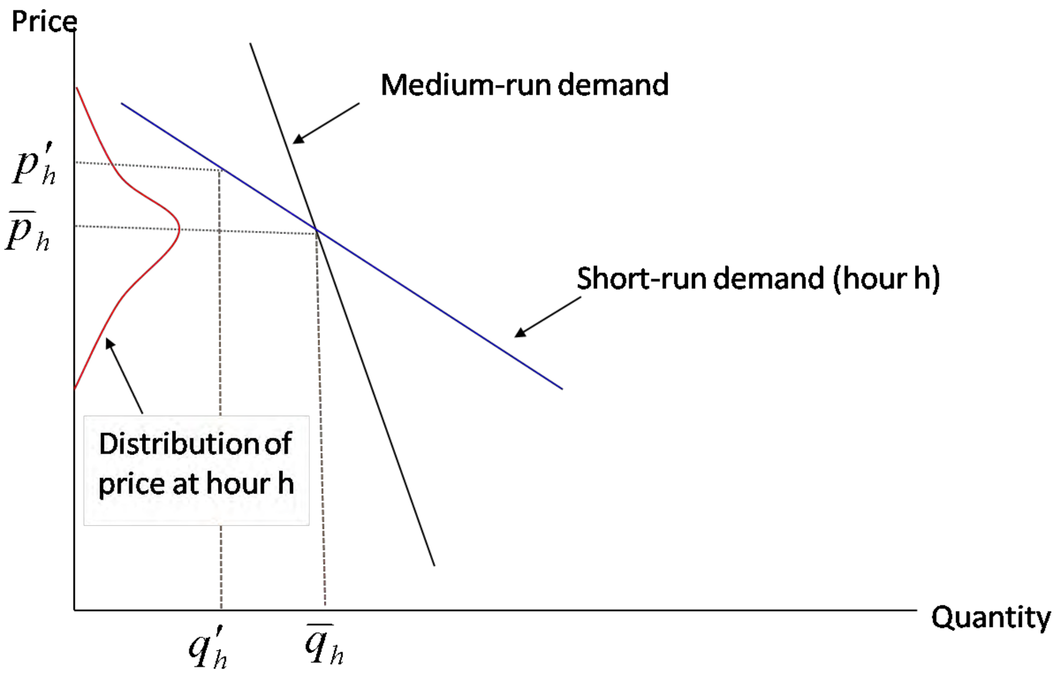
- Even after shifting their daily energy consumption routine to exploit variation in average hourly prices, households can potentially benefit still more **in the short run** –on an hour-to-hour basis—by responding when prices deviate significantly from their hourly means. The extent of the response depends on both the extent of the price deviation and the cost of short-term behavioral adjustments, including the cost of closely monitoring prices. Real-time pricing programs that provide price information cheaply serve to reduce this cost.

In this analysis we focus on medium-run and short-run demand. The relationship between the two is shown in Figure 40. The medium-run demand curve reflects the response of households to the average hourly price. So, for instance, referring to Figure 40, if the average price in hour h is $\bar{p}_h$, the average quantity consumed in the hour is $\bar{q}_h$.

Households may depart from this average consumption in response to deviations in hourly prices from the hourly mean price. Each point on the medium-run demand curve is intersected by a short-run demand curve that captures the response of households to these price deviations at given mean price-quantity levels. The short run demand curve for hour h is presented in Figure 40. If price were to rise to p_h', consumption would fall to q_h'.

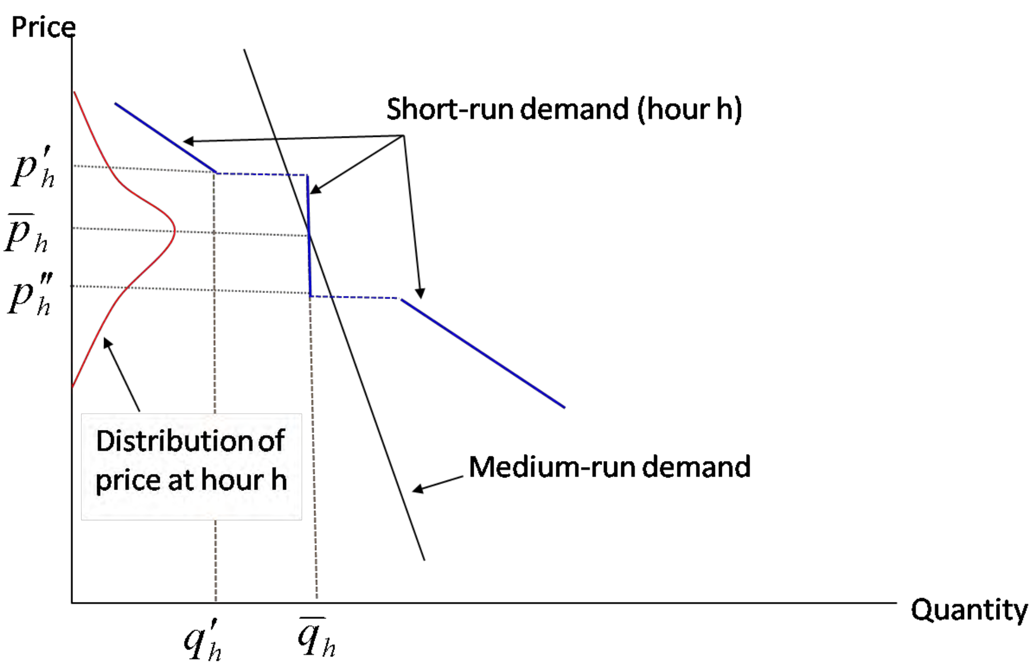
In reality we might expect that short-run demand is essentially inelastic unless the deviation of price from the hourly mean is "large enough" to be perceptible by the households and to make a behavioral change worthwhile. This "demand stickiness" is shown in Figure 41, where short-run demand is infinitely inelastic (vertical) between prices p_h' and p_h'' , and discontinuous at these prices. The hourly standard deviations in Appendix E give some insight as to when we would expect short-run responses to price variation. Price variation was highest in the summer of 2008, especially in the late afternoon and evening hours.

Figure 40. Medium-run and Short-run Household Energy demand



Source: Navigant analysis

Figure 41. Medium-run and Short-run Household Energy Demand when Short-run Demand is "Sticky"



Source: Navigant analysis

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3.3.1 Method for Estimating Medium-Run Demand

Suppose average energy consumption by program participants in hour t, $\bar{y}_{tp}$, takes the semi-log form,

$$\ln \bar{y}_{tp} = \alpha_{0p} + \alpha_1 \bar{\mathbf{X}}_t + \alpha_2 \bar{p}_t + \varepsilon_{tp}, \tag{7}$$

where the vector $\bar{\mathbf{X}}_t$ is a vector of mean values in hour *t* of variables influencing energy consumption, including such variables as an hour-specific constant and average temperature for the hour; and $\bar{p}_t$ is the average price in hour *t*. The counterpart expression for nonparticipants is,

$$\ln \bar{y}_{t,np} = \alpha_{0,np} + \alpha_1 \bar{\mathbf{X}}_t + \alpha_2 p^f + \varepsilon_{t,np}, \tag{8}$$

where p^f is the fixed-rate price of energy. Subtracting (8) from (7) generates the equation,

$$\ln \bar{y}_{tp} - \ln \bar{y}_{t,np} = \tilde{a}_0 + \alpha_2 \bar{p}_t + \tilde{\varepsilon}_t; \tag{9}$$

in this equation, $\tilde{\alpha}_0 = \alpha_{0p} - \alpha_{0,np} - \alpha_2 p^f$.

The price responsiveness of energy consumption is typically measured by the *price elasticity of demand*, defined as the percent change in consumption from a 1% change in price. For the semi-log model presented above, the price elasticity of demand is $\alpha_2 p$, indicating that on a percentage basis, demand is more responsive to price at high prices than at low prices.

An alternative to the semi-log model of energy demand is a log-log model, in which case the price elasticity of demand is constant –the percent change in demand due to a 1% change in price is the same at all price levels. For the log-log model energy demand by participants takes the form,

$$\ln \bar{y}_{tp} = \alpha_{0p} + \alpha_1 \ln \bar{\mathbf{X}}_t + \alpha_2 \ln \bar{p}_t + \varepsilon_{tp}; \tag{10}$$

and energy demand by nonparticipants takes the form,

$$\ln \bar{y}_{t,np} = \alpha_{0,np} + \alpha_1 \ln \bar{\mathbf{X}}_t + \alpha_2 \ln p^f + \varepsilon_{t,np} \quad ; \tag{11}$$

and so the analog to (9) is,

$$\ln \bar{y}_{tp} - \ln \bar{y}_{t,np} = \tilde{a}_0 + \alpha_2 \ln \bar{p}_t + \tilde{\varepsilon}_t \ . \tag{12}$$

Equations (9) and (12) can be estimated via ordinary least squares (OLS) regression for each season, for weekends vs. weekdays, and for various RRTP subgroups (such as RTA-14 and RTA-10 customers), using the mean hourly consumption by the RRTP subgroup of interest as an estimate of $\bar{y}_{tp}$, and the subgroup's baseline mean hourly consumption derived in the hourly regression equations in section 3.2 as an estimate of $\bar{y}_{t,np}$. Assuming the hourly regression models generate unbiased estimates of $\bar{y}_{t,np}$, the estimates of the price coefficient α_2 are unbiased, and therefore the estimates of price elasticities are unbiased.

As discussed in the previous section (see Figure 20 and associated discussion), it appears that program energy savings are positive when prices are high in the summer, and negative when prices are low, indicating, as expected, that demand for energy is downward-sloping. On the other hand, this relationship appears to diminish or even reverse in the winter (see Figure 37), indicating that behavior is not price-responsive in the winter, and that the "rules of thumb" associated with avoiding high prices in the summer remain engaged in the winter. Table 12 presents the correlation between hourly average real time energy price and estimated hourly program savings for winters and summers, 2007-2010. It confirms that in summers hourly prices are positively correlated with hourly program savings, while in winters prices are generally *negatively* correlated with program savings. Consequently we present medium-run price elasticities of demand for summers only, and then briefly discuss the demand estimation results for the program winters.

Table 12. Correlation between hourly mean price and estimated hourly mean RRTP energy savings, winters and summers, weekdays, nonevent days, 2007-2010

	Year			
	2007	2008	2009	2010
Summer				
RT-10 Customers	0.829	0.765	0.726	0.742
RT-14 Customers	0.544	0.513	0.378	0.382
Winter				
RT-10 Customers	-0.244	-0.450	0.068	0.083
RT-14 Customers	-0.303	-0.625	-0.643	-0.421

Source: Navigant analysis

3.3.2 Results: Medium Run Elasticities

Table 13 presents elasticities for summer weekdays, RTA-14 and RTA-10 customers. RTA-14 customers are RRTP program customers receiving the default 14-cent real-time alert, and are the largest subgroup of RRTP customers (see Figure 4 on page 15). RTA-10 customers are those who opted for the more frequent 10-cent alerts, and therefore would be expected to be more responsive to price changes than RT-14 customers, a hypothesis supported by the analysis in section 3.2 indicating that these customers reduce their consumption on summer afternoons considerably more than do RTA-14 households. Whereas the log-log specification of demand imposes a constant elasticity—that is, the regression estimate α_2 *is* the price elasticity of demand—the semi-log specification imposes an elasticity that depends on the observed price, and so for this model we present the elasticity at the mean price for each hour of the season. We present the results for both model specifications, though the semi-log function appears to provide a slightly better fit to the data.

A price elasticity indicates the change in consumption of a good from a 1% increase in its price. So, for instance, with reference to Table 13, the log-log demand model indicates that in summer 2010 a 1% increase in the average hourly price of electricity reduced consumption by RTA-10 customers by an average of 0.22%; stated equivalently, a 10% increase in the average hourly price reduced demand by 2.2%. By contrast, the semi-log model generates the result that price responsiveness is greater at the high-price hours than at the low-price hours. Again referring to Table 13, the semi-log model generates the result that in summer 2010 a 10% increase in average hourly price when the price is $0.063 –the average price at 2 PM –reduced energy consumption by RTA-10 customers by 3.4%.

Analogous results (not shown) were generated for summer weekends and winter weekdays, and these along with the results shown in Table 13 lead to the following overall conclusions:

1. **RTA-10 and RTA-14 Customer Differences:** RRTP customers receiving RT-10 alerts are noticeably more responsive to average hourly price than are customers receiving RT-14 alerts. It bears emphasis that because this pertains to the *average* hourly price, it does not reflect the effect of RT-10 alerts, but rather reflects that RT-10 customers are more likely to alter their consumption behavior to avoid the high price hours. This is consistent with the observation that the customer must request 10-cent alerts, thereby signaling their predisposition to respond to prices.
2. **Weekends:** Medium-run price elasticities are much lower on the weekend. For RTA-14 customers the price elasticity is generally not statistically different than zero, indicating that it is not possible to conclude that such customers do not respond to price on the weekends (perfectly inelastic behavior). For RTA-10 customers the medium-run elasticity is statistically different than zero in three of the four summers (summer 2009 being the exception), but averages about half the value that obtains during the work week.
3. **Winters**: Estimated price elasticities for winter weekdays in 2007, 2009, and 2010 were either not statistically significant, or significant but the incorrect sign, indicating that when price rises, customers respond by using *more* energy. This is consistent with the correlations in Table 12, but is not a reasonable model of behavior. Navigant's best explanation for this result is that many if not most RRTP households focus their attention on avoiding high summer prices in the afternoon, and then fail to realign their behavior to fit the price patterns in winter, when, as shown in Figure 37 on page 53, prices are falling in the afternoon.

Table 13. Price Elasticity of Demand, RTA-10 and RTA-14 Customers, Summer Weekdays (prices in $/kWh)[a]

	2007			2008			2009			2010		
	price	elasticity		price	elasticity		price	elasticity		price	elasticity	
		RTA-10	RTA-14		RTA-10	RTA-14		RTA-10	RTA-14		RTA-10	RTA-14
	Log Model											
	-	-0.18	-0.05	-	-0.08	-0.03	-	-0.14	-0.04	-	-0.22	-0.06
hour ending:	**Semi Log Model**											
1	0.03	-0.13	-0.04	0.03	-0.05	-0.02	0.02	-0.11	-0.03	0.03	-0.17	-0.05
2	0.03	-0.12	-0.04	0.03	-0.05	-0.02	0.02	-0.11	-0.03	0.03	-0.15	-0.04
3	0.02	-0.08	-0.03	0.02	-0.03	-0.01	0.02	-0.10	-0.03	0.02	-0.12	-0.03
4	0.02	-0.07	-0.02	0.01	-0.02	-0.01	0.01	-0.07	-0.02	0.02	-0.11	-0.03
5	0.02	-0.08	-0.02	0.01	-0.02	-0.01	0.01	-0.08	-0.02	0.02	-0.11	-0.03
6	0.03	-0.11	-0.03	0.02	-0.03	-0.01	0.01	-0.09	-0.03	0.02	-0.13	-0.04
7	0.03	-0.13	-0.04	0.02	-0.05	-0.02	0.02	-0.12	-0.04	0.03	-0.15	-0.04
8	0.03	-0.14	-0.04	0.04	-0.07	-0.03	0.02	-0.14	-0.04	0.03	-0.18	-0.05
9	0.04	-0.18	-0.05	0.05	-0.09	-0.04	0.03	-0.16	-0.05	0.04	-0.20	-0.06
10	0.05	-0.21	-0.06	0.06	-0.11	-0.04	0.03	-0.17	-0.05	0.04	-0.22	-0.06
11	0.06	-0.25	-0.08	0.07	-0.14	-0.05	0.03	-0.18	-0.06	0.05	-0.27	-0.07
12	0.06	-0.28	-0.08	0.08	-0.15	-0.06	0.03	-0.20	-0.06	0.05	-0.29	-0.08
13	0.07	-0.30	-0.09	0.09	-0.16	-0.06	0.04	-0.21	-0.07	0.06	-0.30	-0.08
14	0.07	-0.31	-0.09	0.10	-0.18	-0.07	0.04	-0.22	-0.07	0.06	-0.34	-0.10
15	0.08	-0.36	-0.11	0.10	-0.20	-0.08	0.04	-0.24	-0.08	0.07	-0.36	-0.10
16	0.09	-0.37	-0.11	0.11	-0.22	-0.08	0.04	-0.25	-0.08	0.07	-0.38	-0.11
17	0.09	-0.38	-0.11	0.11	-0.22	-0.08	0.04	-0.24	-0.08	0.07	-0.39	-0.11
18	0.08	-0.35	-0.11	0.11	-0.21	-0.08	0.04	-0.24	-0.08	0.06	-0.34	-0.10
19	0.07	-0.30	-0.09	0.09	-0.18	-0.07	0.04	-0.22	-0.07	0.06	-0.30	-0.08
20	0.06	-0.27	-0.08	0.08	-0.16	-0.06	0.03	-0.20	-0.06	0.05	-0.29	-0.08
21	0.07	-0.29	-0.09	0.09	-0.17	-0.06	0.03	-0.19	-0.06	0.06	-0.32	-0.09
22	0.07	-0.30	-0.09	0.09	-0.17	-0.06	0.03	-0.19	-0.06	0.06	-0.33	-0.09
23	0.04	-0.19	-0.06	0.06	-0.12	-0.04	0.03	-0.17	-0.05	0.04	-0.23	-0.06
24	0.04	-0.17	-0.05	0.04	-0.09	-0.03	0.02	-0.14	-0.04	0.04	-0.20	-0.06

[a]In all models of RTA-10 customers, the price parameter that is the basis of the elasticity calculations, α_2, is statistically significant at the .01 level. In all models of RTA-14 customers except the 2009 log model, the price parameter is statistically significant at the .10 level. *Source: Navigant analysis*

3.3.3 Short-Run Elasticity Methodology

Navigant developed a demand system approach to estimating the short-run price elasticities of demand for participants in the RRTP program. This approach corresponds to the notion that electricity consumption under a dynamic pricing program may be considered a time-distinguished good;[16] all else equal, and due to their daily behavior patterns, consumers are willing to pay more for electricity at some times of day than at others. Following this framework, the price elasticity of demand for electricity also varies with the time of day, which necessitates the use of multiple demand equations to capture the changes in price response throughout the day. A demand system facilitates the estimation of separate demand equations, while maintaining the notion that demand at different times of day is interrelated.

Navigant specified the model using the Generalized Almost Ideal (GAI) demand system, where each equation in the system concerns energy consumption in a particular hour or block of hours of the day. Variations of the Almost Ideal demand system are widely used, due in large part to its flexibility and ability to model how a price change for one good (in the current context, energy consumption in a particular hour or blocks of hours) affects consumption of other goods (in the current context, energy consumption in other hours or blocks of hours). The GAI demand system uses daily expenditure shares as the dependent variable, which calls for breaking the day into distinct consumption periods. A natural way to break a day into consumption periods is to cast the household's energy decision problem as one of allocating energy across 24 periods defined as the 24 hours of the day. This can create estimation difficulties, and so, as discussed below, Navigant developed a decision model of 9 distinct consumption time blocks (called simply "blocks" in the discussion below) in a 24-hour day. Conceptually, on each day households allocate their electricity consumption and thus their electricity expenditures across these blocks based on prices and time-dependent consumption needs (such as lighting at night). Theoretically, the customer follows the decision rules of cost minimization and utility maximization.

Formally, in the GAI demand system the share of a day's energy expenditure allocated to time block i is specified by:

$$w_i = \frac{s_i p_i}{x} + \frac{\tilde{x}}{x}\left[\alpha_i + \sum_j \gamma_{ji} \log\left(p_j\right) + \beta_i \log\left(\frac{\tilde{x}}{P}\right)\right] + \varepsilon_i \tag{13}$$

where

- w_i = the day's expenditure share for time block i, defined below;
- s_i = the parameter representing the "pre-committed quantity" for block i ;
- p_i = the day's price ($ per kilowatt-hour [kWh]) for block i;
- x = the day's electricity expenditures;
- $\tilde{x}$ = the day's "supernumerary expenditure", defined below;
- $\alpha_i, \gamma_{ji}, \beta_i$= parameters to be estimated for block i;
- P = the price index for the day, defined below;
- ϵ_i = the error term for block i, resulting from unobserved random variables;

More specifically,

[16] For further discussion, see Price Elasticity of Demand for Electricity: A Primer and Synthesis. EPRI, Palo Alto, CA: 2007, 1016264.

$$w_i = \frac{q_i * p_i}{\sum_j q_j * p_j}$$

$$\tilde{x} = x - \sum_i s_i p_i$$

$$\log(P) = \alpha_0 + \sum_i \alpha_i \log(p_i) + \frac{1}{2}\sum_i \sum_j \gamma_{ij} \log(p_i) \log(p_j)$$

Additionally, the pre-committed quantity (s_i) may be specified as a function of demand shifting variables. Navigant included the cooling degree hours (CDH) for time block i, a binary variable indicating AC cycling event and Load Guard events, and the maximum temperature from the previous day. [17] Finally, in estimation the energy price for block i is the load-weighted average price for the hours composing the block (see below for block definitions).

To ensure the results are consistent with economic theory, Navigant imposed homogeneity and symmetry restrictions via the following set of constraints:

$$\sum_i \alpha_i = 1, \ \sum_i \beta_i = 0, \ \sum_i \gamma_{ij} = 0, \ \sum_j \gamma_{ij} = 0, \ \gamma_{ij} = \gamma_{ji}$$

As mentioned above, it would seem logical to specify each hour of the day as a single time block, thereby generating a set of 24 hourly equations in the GAI demand system. However, the large number of parameters in each equation of the GAI demand system makes this problematic, and so Navigant opted to estimate a system involving blocks of consecutive hours, rather than for each hour individually.[18] This makes sense for several reasons. First, electricity consumption patterns tend to be similar for groups of consecutive hours. Within these groups of hours, there is little variety in the end uses of electricity, and thus the electricity consumed can be thought of as a homogenous good.

Second, we expect little to no price response during the overnight and early morning hours. Given that most customers are asleep during these hours, we do not expect them to make short-run behavioral changes in response to price during this time. Furthermore, the overnight and early morning hours are characterized by low price variation. With relatively stable prices during these hours, customers face prices very similar to their expected prices, leaving little or no room for short-run price response. As the expected price response is low during these hours, Navigant combined the overnight hours into a large block of hours, spanning from midnight to 9 am.

Lastly, electricity prices from hour to hour tend to be correlated. If the price is high at 2 pm on a given day, it is likely to be high at 3 pm as well. A matrix of correlation coefficients for hourly prices is given in Appendix C. Hourly Price Correlation. If consecutive hours have highly correlated prices, little information is lost in combining the hours into a block of hours.

[17] Cooling degree hours are calculated by $CDH = MAX(temperature - 65,0)$. When applied to a block of hours, CDH is calculated for each hour and then summed across the hours within a given block.
[18] The blocks were formed by summing consumption across hours and calculating the consumption-weighted average price. Cooling degree hours (CDH) for the block were calculated by summing the CDH across hours.

Navigant combined the information given by the price correlation coefficients with a general understanding of daily consumption patterns to arrive at the following blocking scheme for use in the GAI demand system:

Block 1:	midnight – 9 am
Block 2:	9 am – noon
Block 3:	noon – 2 pm
Block 4:	2 pm – 3 pm
Block 5:	3 pm – 4 pm
Block 6:	4 pm – 5 pm
Block 7:	5 pm – 7 pm
Block 8:	7 pm – 9 pm
Block 9:	9 pm – midnight

It deserves emphasis that this is a model of *short-run* price responsiveness. The medium elasticity model captures the "rules of thumb" behavioral changes in response to seasonal average prices; the GAI demand system focuses instead on how RRTP households respond to large deviations in prices from their means. Frequently checking electricity prices is time consuming, and the potential gains from doing so are usually quite small. We therefore expect RRTP households to exhibit systematic price responsiveness only on days when the cost of information is low and the potential benefits are high. Such is exactly the case on days with either day-ahead or real-time price alerts. On high price alert (HPA) days, participants are alerted that prices are exceptionally high, creating an opportunity to lower their bill by reducing their load during the high-priced hours. For this analysis, Navigant estimated the GAI demand system using only the 112 HPA days that occurred during the summer months of June, July, and August.[19]

Not all RRTP households make short-run adjustments to prices, even on HPA days. The hourly impact analysis of section 3.2 makes clear, for instance, that RT-10 households are responsive to RT-10 alerts whereas RT-14 households are not (see, for instance, Figure 26 and Figure 28), and of course PA households do not receive direct notification of real time alerts. That RT-10 households appear to be more responsive to high price alerts than RT-14 households is not unexpected given that a household must actively choose to receive RT-10 alerts (because the default price threshold for real time alerts is 14 cents). In light of the previous results we limit estimation of the GAI demand system to RT-10 households on HPA days.

A common approach to measuring the responsiveness of demand to changing prices is the calculation of price elasticities. The price elasticities of demand can be interpreted as:

$$\eta_{ij} = \frac{\%\ change\ in\ Q_i}{\%\ change\ in\ P_j}¶$$

[19] There were 4 HPA days during summer 2007, 76 during summer 2008, 4 during summer 2009, and 28 during summer 2010.

Said another way, if the price increases by 1%, what is the percentage change in load? The elasticity formula derived from the GAI demand system may be found in Appendix D GAI Demand System Price Elasticity Formulas. The expected sign for the own-price elasticity of demand is negative: as the price of electricity increases for a given block, we expect consumption of electricity at that block to decrease, holding all other variables constant.

For the cross-price elasticity of demand, the elasticity may take either a positive or negative value. A positive value indicates that the goods are substitutes: as the price increases for block i, consumption is shifted from block i to block j, resulting in increased consumption during block j. This corresponds to households shifting consumption from one period to the next in response to prices.

Likewise, a negative value indicates that the goods are complements: as the price increases for block i, consumption decreases during block i, causing consumption to decrease during block j as well, due to the complementary nature of the goods. We can think of electricity consumed during two consecutive periods as complementary if the value of the electricity in one period depends on consumption of electricity in the other, as happens when consumption for a particular period "spills over" into a subsequent period. For example, running the dishwasher is an end use that might start in one period and continue into the next period. If the participant decides to forgo washing their dishes due to high prices in the first period, they also reduce their load in the second period. This behavior corresponds to households reducing overall electricity consumption in response to a price increase.

3.3.4 Short-Run Elasticity Results

Table 14 presents the estimated own- and cross-price elasticities from the nine-equation GAI demand system, evaluated at the mean of the data.[20] More detailed information about parameter estimates and model performance can be found in Table 51-Table 52 in Appendix A.

[20] The GAI demand system elasticity formulas are non-linear in form, meaning that the elasticity value varies based on the point of evaluation. In the table above, the elasticities were evaluated at the mean of the data; that is, using the average values of price and quantity. However, if a high or low value for price were used instead of the mean value, the elasticity estimates would change.

Table 14. Short-Run Price Elasticities of Demand, HPA Days, RT-10 Households

Change in Quantity for Block j	Change in Price for Block i								
Hours	**12a-9a**	**9a-12p**	**12p-2p**	**2p-3p**	**3p-4p**	**4p-5p**	**5p-7p**	**7p-9p**	**9p-12a**
12a-9a	-0.223 *	-0.038	-0.022	-0.050	-0.069 *	-0.021	-0.123 *	-0.108	-0.169 *
9a-12p	-0.077 **	-0.156 ***	-0.096 ***	-0.007	-0.005	-0.126 ***	-0.124 ***	-0.151 ***	-0.205 ***
12p-2p	-0.066 **	-0.108 ***	-0.155 ***	-0.001	-0.042 ***	-0.104 ***	-0.181 ***	-0.158 ***	-0.214 ***
2p-3p	-0.165 ***	-0.024	-0.005	-0.290 ***	-0.342 ***	0.035 **	-0.077 **	-0.104 ***	-0.093 *
3p-4p	-0.188 ***	-0.021	-0.063 **	-0.289 ***	-0.312 ***	-0.040 **	-0.015	-0.056 *	-0.092 *
4p-5p	-0.085 *	-0.186 ***	-0.142 ***	0.027 *	-0.038 **	-0.152 ***	-0.215 ***	-0.197 ***	-0.103 **
5p-7p	-0.174 **	-0.104 **	-0.131 ***	-0.034 *	-0.010	-0.114 ***	-0.198 ***	-0.162 ***	-0.178 ***
7p-9p	-0.160 ***	-0.128 ***	-0.121 ***	-0.046 ***	-0.028 ***	-0.111 ***	-0.170 ***	-0.205 ***	-0.065 ***
9p-12a	-0.186 ***	-0.134 ***	-0.127 ***	-0.029 ***	-0.033 ***	-0.039 ***	-0.143 ***	-0.044 *	-0.227 ***

*Statistical significance indicated by: *** $p<0.001$, ** $p<0.01$, * $p<0.05$*

Source: Navigant analysis

The own-price elasticities, found along the diagonal and shaded dark brown, are all negative, as expected. Recall that price elasticities are interpreted as the percentage change in quantity demanded for a percentage change in price. For example, to investigate the effect on load of a price increase from 2–3 pm, look at the "2–3 pm" column. Reading down this column gives the percentage change in load throughout the day. Looking at the cell on the diagonal, the elasticity of -0.290 indicates that a 1% increase in the price from 2–3 pm reduces the load at 2-3 pm by 0.29% percent. Put another way, a 10% increase in price will reduce the load by 2.9%.

Some of the own-price elasticities reported in Table 14 are larger than estimates reported elsewhere in other studies. This is not unexpected. The elasticities estimated using the GAI demand system represent *short- run* price response to substantial deviations in price on HPA days. Moreover, elasticity analyses using a single demand equation, as is usually done in the industry, implicitly assumes that demand does not shift throughout the course of the day as one would expect to be the case in light of daily behavioral routines (sleeping at night, returning home from work in the late afternoon or early evening). This is shown by the black dashed line in Figure 42. In reality, though, the demand for energy changes during the course of the day, as shown in the figure. A single demand equation essentially conflates several distinct demand equations –the equations associated with time-dependent preferences for energy consumption—in a single, misidentified equation. In general, because demand tends to be high at the times of day when prices are high, the result is the underestimation of price elasticity of demand.