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Request IR-1:

ELI customers completed efficiency projects in 2009 and 2010. The resulting energy and demand savings contribute to the IRP targets and are reported in this filing because they are incremental to customer-funded DSM and were not included in the 2009 IRP Update. The cumulative ELI energy and demand savings are estimated to be 80 GWh and 20 MW. These estimates are based on a preliminary investigation completed on behalf of ENSC by third party specialists and, as such, are necessarily conservative. These projects will undergo evaluation in 2011. Variances between estimates and final verified results will be reported in the filing of the 2013 DSM Plan. (p.15)

Please provide information with respect to the inclusion of electricity savings by the Extra Large Industrial class (ELI). When was ENSC notified of these unexpected ELI savings? Were there meetings between ENSC and ELI? Who was at the meetings? When were other stakeholders notified of these changes to the 2012 DSM plan?

Response IR-1:

On January 7, 2011, at the second stakeholder conference on 2012 DSM planning, the ELI representative advised ENSC and all stakeholders about significant incremental electricity savings by the ELI class and inquired about their inclusion in the DSM Plan. ENSC responded at that session that these savings could be considered for the 2012 DSM Plan if sufficient independent verification could be completed in time for the filing deadline. Subsequently, ENSC was invited and did meet with a broad group of stakeholders on January 20, 2011, comprised of representatives from the Consumer Advocate, ELI Class (NewPage Bowater), Large Industrials (Avon Group) and the Municipal Electric Utilities, to gain a better understanding of the energy saving activities, magnitude and their proposed inclusion in the DSM Plan.

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Following this meeting, ENSC engaged an industry specialist, Energy Performance Services (EPS/Canada) Inc., to review the energy saving projects, perform site visits at the customers' facilities and provide ENSC with an independent preliminary verification and estimate of the savings. ENSC and its consultants then included conservative savings estimates from those provided by the independent industry specialist in the final development of the 2012 DSM Plan. All stakeholders were notified of these adjustments on February 28, 2011 on filing of the final 2012 DSM Plan with the UARB.

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Request IR-2:

Please explain how ENSC would have planned to achieve 80 GWh of energy savings in the absence of the unexpected savings from ELI.

Response IR-2:

In the absence of 80 GWh and 12 MW of electricity savings from the ELI class, ENSC's preliminary estimates were that it would require an investment of $56.1 million to meet the cumulative IRP energy savings target to 2012. Please refer to EAC IR-22, Attachment 1, Slide 51.

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Request IR-3:

Please provide information, such as a verification report, with respect to the unexpected energy savings from the large industrial class. Please detail what preliminary investigation (and by whom) has projected this level of energy savings from ELI.

Response IR-3:

Please refer to Multeese IR-8.

Request IR-4:

Based on the advice received, ENSC considers the proposed program savings targets and investment to be both challenging and achievable. The Plan is consistent with the Integrated Resource Plan (IRP) savings targets, as updated in 2009… The proposed 2012 DSM Plan meets the energy savings targets within the level of investment identified in the 2007 IRP and the 2009 IRP Update filed with the UARB. (p.4)

"The proposed investment for 2012 is $43.7 million. With the inclusion of electricity savings by others, ENSC has been able to exceed the IRP savings targets for 2012 while keeping the investment for electricity savings close to the 2011 level and below the IRP target program cost of $61 million… It is anticipated that continued work with stakeholders will allow ENSC the flexibility to make appropriate mid-course adjustments to the programming mix to achieve the total energy and demand savings targets." (p.13)

Please provide information and clarification with regards to how ENSC will pursue mid-course adjustments to DSM and how this relates to ENSC interests in performance-based accountability and regulation.

Response IR-4:

Mid-course adjustments to programs by the Administrator for 2008-2011 have been reviewed with the PDWG. ENSC sees value in having the PDWG continue its role in 2011, receiving periodic progress reports on DSM programs, and advising ENSC on the design of new programs and any mid-course adjustments, based on program results or changing circumstances.

ENSC is committed to broad, transparent and effective stakeholder consultation. As directed by the UARB in its 2011 DSM Plan Decision, ENSC is now engaged with members of the PDWG

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in a review of the role and composition of the PDWG.[1] A broader group of stakeholders will be consulted in 2011 to gain thoughts on potential changes to the PDWG and/or the possible creation of a new stakeholder process.

For how this relates to performance-based accountability and regulation, please refer to Multeese IR-14.

[1] [2010] NSUARB 153, para. 113: "The Board accepts that the PDWG should retain its current role until the transition to ENS is completed. At that time, ENS can then determine whether the continuation of the PDWG, or another committee, would be appropriate."

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Request IR-5:

Please provide detailed reasons about how and why ENSC has chosen to pursue a different level of investment in the ENSC 2012 DSM Plan versus what was identified as reasonable in the 2007 IRP and the 2009 IRP Update (a difference of 17.3 million).

Response IR-5:

ENSC's 2012 DSM Plan meets the electricity savings targets in the 2009 IRP Update. ENSC does not consider that the nominal budget identified in the IRP is prescriptive for program planning, or that GWh and MW savings should be based on set expenditures.

Accordingly, ENSC has developed its 2012 DSM Plan aimed at meeting the GWh and MW targets in the IRP.

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Request IR-6:

Please provide information with regards to the level of energy savings achievable if the IRP budget for DSM were fully spent.

Response IR-6:

Please refer to EAC IR-22, Attachment 1, Slide 51.

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Request IR-7:

Please provide the IRP load forecast with respect to DSM and the estimates for economic and achievable energy savings from the IRP.

Response IR-7:

Please refer to NPB IR-1.

The figure below provides estimates of achievable DSM energy savings as identified in the 2009 IRP Update. The 2009 IRP Update did not include forecasts of DSM economic potential.

TOTAL	Incremental Achievable Potential Demand Savings (MW)	Cumulative Demand Savings (MW)	Incremental Achievable Potential Energy Savings (GWh)	Cumulative Energy Savings (GWh)
2008*	2		16	
2009*	7	9	50	66
2010**	17	26	83	149
2011***	31	57	146	295
2012***	44	101	205	500
2013***	63	164	305	805
2014***	57	222	276	1,081
2015***	57	279	276	1,357
2016***	57	336	276	1,632
2017***	56	392	268	1,901
2018***	54	446	261	2,162
2019***	53	500	255	2,417
2020***	52	551	249	2,666
2021***	51	602	243	2,909
2022***	50	652	238	3,148
2023***	49	700	233	3,381
2024***	48	748	229	3,610
2025***	47	795	225	3,834
2026***	46	841	221	4,055
2027***	45	886	217	4,273
2028***	45	931	214	4,487
2029***	44	976	211	4,698
2030***	44	1,019	209	4,907
2031***	43	1,063	206	5,113
2032***	43	**1,106**	204	**5,317**

Notes:
The numbers in this table may not sum exactly due to rounding.
* Approved Programs (expressed in 2008 dollars)
** Proposed 2010 DSM Targets (expressed in 2010 dollars)
*** Potential DSM Investment in future years (expressed in 2010 dollars)

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Request IR-8:

ENSC DSM Plan 2012 states, "The 2010 expenditures include $1.55 million in startup costs for ENSC to set up the organization, transition responsibility and operations from NSPI and develop the 2012 DSM Plan. The startup budget approved by the UARB in June 2010 was $2.04 million, for expenditures in 2010 and 2011." (p.9)

Does ENSC anticipate start-up costs or learning costs for the organization in 2012?

Response IR-8:

ENSC does not anticipate start-up costs in 2012.

ENSC will have learning costs in 2012 and expects to always have a continuous learning culture associated with the redesign and implementation of existing programs as well as the design and implementation of new programs.

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Request IR-9:

ENSC DSM Plan 2012 (p.14)

	2012 Investment ($ Million)	Lifetime Benefits ($ Million)	Incremental Annual Net Energy Savings at Generator (GWh)	Incremental Annual Net Demand Savings at Generator (MW)	Total Resource Cost Test (TRC)	Program Administrator Cost Test (PAC)
Overachievements from 2008-09 DSM Plans						
	n/a	n/a	19.5	6.1	n/a	n/a
Enabling Strategies						
Education & Outreach	2.0	n/a	n/a	n/a	n/a	n/a
Development and Research	1.5	n/a	n/a	n/a	n/a	n/a
Other Enabling Strategies	1.5	n/a	n/a	n/a	n/a	n/a
Residential DSM Programs						
Efficient Products	4.0	13.3	17.4	2.6	1.9	3.3
Existing Houses	9.7	24.3	14.1	4.2	1.9	2.5
New Houses	4.3	10.0	5.6	1.5	1.5	2.3
Home Energy Report	0.9	1.3	13.0	3.0	1.5	1.5
Commercial & Industrial DSM Programs						
Prescriptive Rebate	4.5	22.5	21.5	4.2	2.7	5.0
Custom	9.2	47.6	37.9	5.4	2.1	5.1
Small Business Direct Install	6.0	16.7	14.7	2.3	2.1	2.8
Savings Outside ENSC DSM Programs						
Extra Large Industrial Projects			80.0	12.0		
Adoption of Codes and Standards			10.0	2.7		
TOTAL	43.7	135.7	233.6	44.0	1.9	3.1

Please confirm that 4 million will be spent on enabling strategies. Please explain why enabling strategies are important to the future success of ENSC DSM programs in Nova Scotia.

Response IR-9:

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ENSC's plan includes $2 million for education and outreach activities, $1.5 million for development and research and $1.5 million for other enabling strategies, for a total of $5.0 million in enabling strategies.

Enabling strategies are important for two reasons: they can support and strengthen programs in the short term and they can generate value toward long-term goals. For example, provision of workforce training can support the market's ability to provide quality DSM services in the future, both in response to, and outside of, specific program efforts. Similarly, effort spent today on developing innovative financing solutions is intended to lead to implementation of those solutions in the future and, as a result, higher measure uptake and/or reduced program costs.

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Request IR-10:

Please confirm that the Home Energy Report (4.7% of the residential budget) is expected to deliver 26% of the GW/h savings and 26.5% of the MW savings in the residential sector programming.

Response IR-10:

Confirmed.

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Request IR-11:

Please explain what baselines assumptions have been made to project this level of energy savings from the Home Energy Report, at the level of investment relative to the total residential budget.

Response IR-11:

Baseline assumptions include:

- Annual energy savings of 201.4 kWh, corresponding to 1.5 percent of annual energy use

- 64,420 participating households

- Program budget of $901,875

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Request IR-12:

Please provide any further evidence with regards to the projected GWh savings estimates for the Home Energy Report (including examples from other jurisdictions).

Response IR-12:

Please refer to Attachments 1-5 for Home Energy Report energy savings estimates in other jurisdictions.

Energy Conservation "Nudges" and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment

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Abstract

JEL Codes: Q41, D03, D72

Energy Conservation "Nudges" and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment

"Nudges" are being widely promoted to encourage energy conservation. We show that while the electricity conservation "nudge" of providing feedback to households on own and peers' home electricity usage works with liberals, it can backfire with some conservatives. Our regression estimates predict that a registered liberal who pays for electricity from renewable sources, who donates to environmental groups, and who lives in a liberal neighborhood reduces consumption by 3.1 percent in response to this nudge. A registered conservative who does not pay for electricity from renewable sources, who does not donate to environmental groups, and who lives in the bottom quartile liberal neighborhood increases consumption by 0.7 percent.

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Europe, especially Scandinavia, has high taxes on electricity and gasoline to encourage conservation and counter global warming. Taxes in Denmark represent more than half of the cost of electricity to consumers.[1] In contrast, the U.S. has low taxes and little political will to sacrifice for the sake of conservation. Congressional voting patterns highlight that conservative Representatives whose districts have low per-capita income are highly unlikely to vote for carbon mitigation legislation (Cragg and Kahn 2009). "Nudges" therefore have been promoted as a politically palatable alternative to higher taxes, stricter building codes, and clean energy mandates (Allcott and Mullainathan 2010; Thaler and Sunstein 2008). In the UK, where electricity taxes are low, David Cameron has touted the behavioral transformations from putting "the typical electricity bill for a house like theirs in a neighbourhood like theirs" in front of households.[2]

We find that the effectiveness of energy conservation "nudges" depend on an individual's political ideology. In the United States, Democrat, Peace and Freedom, and Green party members (liberals in the U.S. terminology) are more likely to vote for environmentalist causes than Republican, American Party, or Libertarian party members (conservatives in the U.S. terminology). Although liberals and environmentalists are more energy efficient than conservatives (Costa and Kahn 2010), thus making it harder for them to reduce consumption further, we find that liberals and environmentalists are more responsive to these nudges than the average person. In contrast, for certain subsets of Republican registered voters, we find that the

[1] See Eurostat News Release, 75/2010 – 28 May 2010. http://epp.eurostat.ec.europa.eu/cache/ITY_PUBLIC/8-28052010-AP/EN/8-28052010-AP-EN.PDF
[2] Speech of June 13, 2008. http://www.aletmanski.com/files/**davidcameron**-powerofsocial-innovation.doc

specific "treatment nudge" that we evaluate has the unintended consequence of increasing electricity consumption.

Our evidence on the role of ideology in energy conservation "nudges" comes from a randomized field experiment carried out by a large California utility district. Starting in Spring 2008, it has been sending households in the treatment group a Home Energy Report (HER). The report provides household specific information on own monthly electricity usage over time and relative to neighbors' usage over the same time period. The report provides energy saving tips. To examine the role that political ideology and environmentalism play in determining how randomly selected households respond to these reports, we have collected data on individual political party of registration, household donations to environmental organizations and household participation in renewable energy programs, and data on the characteristics of the local residential communities where the households live. Households who are registered in liberal political parties and who live in residential communities with a large liberal share and who have previously signed up for energy from renewable resources and donate to environmental causes are arguably environmentalists. This observable variation is crucial in distinguishing our estimation strategy from previous studies that have focused on estimating average treatment effects.

Recent field experiment research has suggested that direct peer comparisons can be effective at changing household electricity consumption. Allcott (2009) , Ayers, Raseman, and Shih (2009), and Schultz et al. (2007) found that providing feedback to customers on home electricity and natural gas usage with a focus on peer comparisons decreased consumption by 1 to 2 percent, potentially saving 110 million kWh per year if feedback were provided to all of the utility's customers (Ayers et al. 2009). When California initiated a media campaign in 2001 to promote voluntary conservation, consumption in San Diego declined by 7% during the initial two phases of the campaign, before rebounding. The declines were as large as those achieved through an unexpected doubling of the electricity prices, without the resulting political outcry that led to a cap on prices (Reiss and White 2008).

By documenting the role that ideology plays in determining the effectiveness of a well known "nudge", this paper contributes to the growing literature on the consequences of political ideology. Recently there has been extensive work on the determinants of political ideology. Researchers have examined the causal role of the media (DellaVigna and Kaplan 2007), property rights (Di Tella, Galiani and Schargrodsky 2007), and historical circumstances (Alesina and Fuchs-Schundeln 2007; Giuliano and Spilimbergo 2009) in shaping a person's ideological outlook. Akerlof and Kranton's (2001, 2010) work on identity provides another possible mechanism: individuals might embrace a specific ideology to "fit in" with their community. In this study, we will take as given that a household either is or is not a liberal/environmentalist and we will study how these political and social views influence household response to the same randomized treatment.

European studies have highlighted the role that environmental ideology plays in determining the willingness to take voluntary actions to mitigate one's carbon externality and the willingness to pay to purchase a "green product". Thalmann (2004) and Halbheer, Niggli and Schmutzler (2006) document that voters who are left-of-center or who are environmentalists were more likely to vote for Swiss environmental referenda. Brounen and Kok (2010) found that the price premium for residential homes that are certified as highly energy efficient in Holland is higher in "green" communities, that is communities where the Green Party and the Party for the Animals had received a larger fraction of the vote. U.S studies have also documented that environmentalists are more likely to participate in green markets ranging from green power programs and purchasing green vehicles such as the Prius (Kotchen and Moore 2004, Kahn 2007, Kahn and Vaughn 2009).

If environmental ideology plays a role in mediating how heterogeneous households respond to a randomized treatment, nudges need to be tailored to the household. Mixed messages, for example, one for left-of-center and one for right-of-center households, may be needed to encourage a diverse population to take socially beneficial actions.

Economic Framework

Within a household production framework, a household values electricity as an input in producing comfort (e.g. indoor temperature) and leisure and household production activities . Total household electricity consumption in any given period is the sum of electricity used in each of these activities. A household's total electricity consumption depends on choices over 1) the attributes of the house, such as size; 2) the attributes of appliances; and 3) the intensity of utilization of appliances for leisure and household activities, indoor temperature control and illumination. These choices, in turn, depend on climate, prices and personal attributes, including ideology.

The Ideological Divide over Environmental Issues

We view environmental ideology as a set of prior beliefs including those about the importance of energy conservation. The ideological divide on environmental issues between Democrats and Republicans will affect how a household responds to an energy conservation "nudge." In the United States, conservatives consistently oppose environmental regulation and energy policies intended to further environmental aims. This claim is based on evidence from polling on the belief in climate change (Dunlap and McCright 2008) and Congressional voting patterns (Cragg and Kahn 2009). Rising polarization between Democrats and Republicans has been well documented and environmental issues are a leading case.[3] Dunlap and McCright (2008) report that in 2008 there was 34 percentage point gap between Democrats and Republicans in their agreement with a statement that the effects of global warming have already begun, up from a 4 percentage point gap in 1997. The 2008 National Environmental Scorecard of the League of Conservation Voters gives the House Democratic leadership a score of 95 (out of a best score of 100) and the Republican leadership a score of 3.[4] A 2009 Pew survey found a 23 percentage gap between Democrat and Republican agreement with the statement that people should be willing to pay higher prices to protect the environment. Prescriptions for energy policy differ between Democrats and Republicans: 88 percent of Republicans favor drilling in U.S. waters compared to 56 percent of Democrats.[5] The two word phrase "fuel efficiency" was one of the top phrases used by Congressional Democrats but not by Republicans (Gentzkow and Shapiro 2010). Republicans and Democrats respond differently to “carbon offsets” versus “carbon tax” (Hardistry, Johnson, and Weber 2010), suggesting that ideology moderates how individuals think of key words.

The “Nudge”

The “nudge” that the electric utility company sends to treatment households in an on-going randomized experiment to encourage reductions in electricity consumption is a two page Home Electricity Report (see Appendix A for a sample). Similar reports have been used by

[3] See Keith Poole’s web site, www.voteview.com .
[4] See http://www.lcv.org/2008-pdf.pdf .
[5] See Independents Take Center Stage in Obama Era: Trends in Political Values and Core Attitudes: 1987-2009, May 21, 2009, http://people-press.org/report/517/political-values-and-core-attitudes .

other utilities in the U.S. The front page compares the electricity consumption of the household with all neighbors with similar size homes and heat type and with neighbors who are in the bottom 20th percentile of electricity usage. The back page compares the household's electricity usage in the current month relative to the same time month in the prior year and awards green stars in every month the household consumed less relative to the same month in the past year (panel not shown in Appendix A because it is not publicly available). It also provides three tips for saving energy, such as turning down the thermostat when using an electric blanket or purchasing an Energy Star durable, and indicates the dollar amount in energy savings per year (shown in Appendix A). Each report contains two pieces of information: the household's absolute level of consumption and how it compares with its neighbors. Because the correlation between baseline own and relative consumption is 0.7, we cannot separately identify the impact of these two pieces of information.

We view the receipt of a Home Electricity Report as intent to treat. A household could refuse treatment either by opting out of receiving future reports (an action requiring either a phone, email, or written mailed request and thus one taken by few households) or by not reading the report. In this evaluation framework, ideology determines both whether a household decides to take the treatment and, if it takes the treatment, its response to the treatment (i.e. turning up the thermostat in summer or buying more energy efficient durables).

The HER Experiment

Between March 14 and May 9 2008, the electric utility sent the first Home Electricity Reports to a treatment group of approximately 35,000 households. By April 1, 43% of all treatment households had received the report and by April 15 the figure was 62%. Households are still receiving the report, either on a quarterly or monthly basis. A control group of roughly 49,000 households have never received a Home Electricity Report.

The HER experiment selected households from 85 census tracts with a high density of single-family homes (see ADM Associates 2009). Both treatment and control households had to have a current account with the electric utility that had been active for at least one year, could not be living in apartment buildings, and had to be living in a house with square footage between 250 and 99,998 square feet. Groups of contiguous census blocks were randomly assigned to either the treatment or control group. A "block batch" of 5 contiguous census blocks was randomly assigned to the treatment group and then a contiguous census block batch was assigned to the control group. The process continued until roughly 35,000 households were assigned to both the treatment and control groups. The remaining census blocks (14,000 homes) were assigned to the control group. Contiguous block groups were used because the implementation contractor, Positive Energy (now OPOWER), believed that increased communication among people receiving the Home Electricity Reports in the same community would lead to greater energy savings.[6]

Data

Our primary data set consists of residential billing data from January 2007 to October 2009. These data provide us with information on kilowatt hours purchased per billing cycle, the length of the billing cycle (measured in days), whether the house uses electric heat, and whether the household is enrolled in the electric utility's program to purchase energy from renewable

[6] In a 2009 Home Energy Use Survey conducted by the electric utility, households in the control group were more likely to report talking to friends and neighbors about their electricity bill than households in the treatment group, suggesting that receiving the Home Energy Report did not inspire discussion and that any positive peer effects operate through implicit social pressure.

sources. We link each billing cycle to the mean daytime and nighttime temperature in that billing cycle.[7]

We link the billing data to the treatment and control data which contain information on when the household began to receive the Home Energy Reports, as well as information on square footage of the house, information on whether the home heats with electricity or natural gas, and the age of the house. The treatment and control data contain 48,058 households in the control group. Among the households in the treatment group, 24,028 received a monthly report and 9,636 received a quarterly report.

We merge individual voter registration and marketing data for March 2009 to our data set.[8] For registered voters we know party affiliation, level of education, and whether the individual donates to environmental organizations. We were able to link half of our sample to the voter registration data. We linked either the person whose name was on the utility bill or the first person on the utility bill.[9] The individuals we could not link were living in smaller households and in block groups with a low proportion of the college-educated, were more likely to receive a subsidy for electricity because of their low income, and were more likely to have a household head above age 60.[10] We also merge to these data, by the block group, the share of registered voters who were liberal (Democrat, Green, or Peace and Freedom) in 2000 and the

[7] Two different households in the same calendar year and same month who are on different billing cycles will face *different* climate conditions and electricity prices. Any two households on the same billing cycle will face the same average temperature but since different households are on different billing cycles within the same month, we have within month variation in climate.

[8] We purchased the data from www.aristotle.com.
[9] Only 5% of households were "mixed" between conservatives and liberals.
[10] Relative to all homeowners in the same county these individuals were also more likely to be of Asian or other ancestry rather than of European ancestry, but were less likely to be Spanish speaking. They were also lower income.

share of the college-educated in the block group. We expect that environmentalists are more likely to live in liberal, educated communities.

We have access to two other revealed preference measures of a household's environmentalism. From the data base with voter registration information, we know whether a household has donated money to an environmental group. We also know whether the household has signed up for the company's renewable power program prior to the treatment. This is the electric utility's major program to increase the share of its customers who have signed up for renewable energy. Each household decides whether to opt in and pay a fixed cost of $3 a month to have 50% of its power generated by renewables or $6 a month to have 100% of its power generated by renewables.[11]

We also have access to an ancillary data set. In 2009 the electric utility company surveyed 1,375 households who received the HER, asking them questions about the HER report. We restrict this sample to households for whom we have information on age and the fraction of liberals in the block group and to households who were not in minor parties we could not classify as liberal or conservatives. This leaves us with 1061 observations in this ancillary data set.

Table 1 shows that the treatment and control groups are roughly representative of all homeowners in the county in terms of household and neighborhood characteristics. But, there are some clear differences. The treatment and control groups consume roughly 10% more electricity than the average county homeowner as of 2007 (before the experiment). Relative to the average homeowner, the experiment homes are older and more likely to be electric homes. The households in the experiment group are roughly 10% richer than the average county

[11] The collected revenue is used by the electric utility to purchase and produce power from wind, water, and sun.

homeowner.[12] The geographical areas included in the experiment have a much higher share of college graduates than the average county home owner's community.

The randomization of the HER across blocks was effective. Ayers et al. (2009) reported that controlling for house characteristics, household demographics, and the number of cooling degree days and heating degree days, there was no systematic difference in energy usage between treatment and control groups prior to the treatment. Households living in electric homes were more likely to receive a monthly rather than a quarterly report.[13]

Econometric Framework

Previous studies have examined the HER report's average treatment effect and have also examined how its effect varies by standard characteristics such as attributes of the home and socio-economic characteristics of the owner. The distinguishing feature of this study is our emphasis on household environmental ideology as an important determinant for how households respond to well-meaning new information.

Many households will read the report for non-ideological reasons, such as wanting to lower their bill. These households, regardless of ideology, may reduce their consumption. But perverse effects could happen here too. A household mainly concerned with the size of its electricity bill may increase its consumption if it learns that the savings from conservation are relatively modest (e.g. if it learns that by being "smart" about heated blankets and pads it can

[12] Household income is available from credit bureau data.
[13] Geographical areas were randomly assigned to the treatment group or the control group. Within a treated geographic area households received either a monthly or quarterly report. Roughly 71% of households received the monthly report. Households with a low baseline electricity consumption received the quarterly report while households with a high baseline electricity consumption received the monthly report. Conditional that a household's daily average electricity consumption was less than 20 kWh per day it had a 2.5% chance of receiving the monthly report. Households whose 2006 electricity consumption was greater than 23 kWh per day had a 99% chance of receiving the monthly report.

save at most $10 per year). A household that realizes it is below the neighborhood average in consumption may increase its consumption. This "boomerang effect" is discussed in Allcott (2009) and Ayers et. al. (2009).

Environmentalist households may read the report because they want to lower their consumption. Conservative households may read the report if they are suspicious of all green initiatives. Once a household decides to accept the treatment, it responds to the treatment with varying levels of intensity. An environmentalist household interested ex-ante in lowering its consumption may decrease its electricity consumption unless the report contains no "new news". An avid environmentalist household may have engaged in the time intensive activity of tracking its own monthly electricity consumption and talking to neighbors about their consumption. In this case, the HER may have no behavioral impact on this "green group." Conversely, a household that is adamantly anti-environmentalist may pride itself on increasing its consumption. Because people find information more reliable when it conforms to their strong prior beliefs (e.g. Lord, Ross, and Leper 1979; Miller et al. 1993; Munro and Ditto 1997; Gentzkow and Shapiro 2006, 2010) and are influenced mainly by those in their network (Murphy and Shleifer 2004), the receipt of a report that looks "green" may inspire anger.

We estimate intent-to-treat effects (which we will simply refer to as treatment effects) of receiving the HER by running regressions of the form:

1) $\ln(kWh) = \beta_0 + \beta_1(Household\ FE) + \beta_2(Month/Year\ FE) + \beta_3(Temp, Electric) + \beta_4 TREAT + \varepsilon$

2) $\ln(kWh) = \beta_0 + \beta_1(Household\ FE) + \beta_2(Month/Year\ FE) + \beta_3(Temp, Electric) + \beta_4 TREAT + \beta_6(TREAT \times Party\ Registration) + \beta_7(TREAT \times Green\ Indicators) + \varepsilon$

3) $\ln(kWh) = \beta_0 + \beta_1(Household\ FE) + \beta_2(Month/Year\ FE) + \beta_3(Temp, Electric) + \beta_4 TREAT + \beta_6(TREAT \times Party\ Registration) + \beta_7(TREAT \times Green\ Indicators) + \beta_{10}(TREAT\ \times College\ Graduate) + \beta_{11}(TREAT\ \times Block\ Characteristics) + \varepsilon$

4) $\ln(kWh) = \beta_0 + \beta_1(Household\ FE) + \beta_2(Month/Year\ FE) + \beta_3(Temp, Electric) + \beta_4 TREAT + \beta_6(TREAT \times Party\ Registration) + \beta_7(TREAT \times Green\ Indicators) + \beta_{10}(TREAT\ \times College\ Graduate) + \beta_{11}(TREAT\ \times Block\ Characteristics) + \beta_{12}(TREAT\ \times House\ Characteristics) + \varepsilon$

where TREAT is a dummy equal to one if the household received the treatment effect, that is, if the household received the Home Energy Report.

In all regressions we control for household and month/year fixed effects, a cubic in mean daily temperature within the billing cycle, and an interaction of the cubic mean daily temperature with a dummy indicator if the house is an electric house (Temp, Electric).[14] We cluster the standard errors on the household to account for autocorrelation in monthly electricity consumption (Bertrand, Duflo, and Mullainathan 2004). We assume that there are no contemporaneous shocks to each contiguous block batch group after controlling for month/year fixed effects, household fixed effects, and average billing cycle temperature.[15]

The first regression estimates a treatment effect with no heterogeneous responses. The second regression adds treatment effects by political party registration: liberal (Democrat, Green, or Peace and Freedom) no party affiliation, other party, and not registered, with conservative (Republican, American Party, and Libertarian) as the omitted dummy variable.

[14] Although we allow the treatment effect to vary by education level, we do not interact the treatment effect with the household's income level because Allcott (2009) found that treatment effects do not vary by income.
[15] This assumption would break down if temperature shocks were specific to a block batch group. There is no significant climate zone variation within the electric utility's service area.

The fourth regression allows for additional treatment effects by whether the household purchases energy from renewable sources and whether the household donates money to environmental causes (Green Indicators). The fifth regression additionally allows for differential treatment effects by whether the household is college-educated and by the block characteristics of the share of college educated and of liberals (Democrats, Greens, and Peace and Freedom) in the census block group. The sixth regression also allows for differential treatment effects by the type of house: the logarithm of square footage, the logarithm of the age of the house, and whether the house is an electric house.

We examine who accepts treatment by estimating, for the treatment group, a probit regression of the form

$$OptOut = \beta_0 + \beta_1 High + \beta_2 \ln(Usage) + \beta_3 Age + \beta_4 Liberal + \beta_5 Unregistered + \varepsilon$$

where OptOut is a dummy variable equal to one if the household opts out of receiving the treatment, High is a dummy variable equal to one if the household's consumption is above the neighborhood average, Usage is the household's electricity usage in 2006, Age is the age of the head of the household, Liberal is a dummy equal to one if the household head was registered as either a Democrat, Green, or Peace and Freedom party member, and Unregistered is a dummy equal to one of if the household was not registered.

We also examine who, in the treatment group, found the reports of no value or disliked the reports by estimating probit regressions of the form

$$\begin{aligned} &Report\ Reaction \\ &\quad = \beta_0 + \beta_1 High + \beta_2 \ln(Usage) + \beta_3 Age + \beta_4 Liberal + \beta_5 Unregistered + \varepsilon \end{aligned}$$

where Report Reaction is either a dummy variable equal to one if the household found the reports of no value (responses of not at all or not very valuable) or a dummy variable equal to one if the household disliked the reports (responses of did not like or indifferent).

As shown in equations (1 to 4), we are estimating the effect of a treatment (receiving the HER report) with conditional average treatment effects on electricity demand. The heterogeneous treatment effects by political affiliation that we focus on are consistent with an interesting identity story.

Results

Table 2 shows the mean overall treatment effect and the treatment effect by own and neighborhood ideology, own and neighborhood education, and house characteristics using specifications 1-4. We obtain a mean overall treatment effect of -0.021 (see regression 1).[16]

The second regression in Table 2 show that own ideology, whether measured by political party affiliation, donations to environmental organizations, or the purchase of green energy, is associated with differential treatment effects. A registered conservative will decrease mean daily kWh by only 0.4 percent in response to the treatment but a registered liberal will reduce consumption by 1.1 percent. Unregistered voters have a large response to the treatment effect: the treated reduce their consumption by 2.9 percent relative to registered conservatives. Those purchasing energy from renewable resources reduce their consumption by 1.5 percent relative to

[16] We also have information on household monthly expenditure on electricity. In the presence of an increasing block tariff structure, some recipients of the Home Energy Report may reduce their expenditure by more than their electricity consumption. This is possible for those whose consumption (before receiving the HER) just places them on an upper pricing tier. For this group, small reductions in electricity consumption can lead to larger reductions in electricity expenditure. We have estimated regressions similar to equation 4 in which we use the log of household monthly electricity expenditure as the dependent variable. We obtained very similar results on ideology and found positive treatment effects for one quarter of the sample.

those not purchasing green energy. Those donating to environmental organizations reduce their consumption by 1.0 percent.

The third regression shows that community characteristics affect the treatment response, independent of own characteristics. This specification adds own education, the fraction of liberals in the block group, and the fraction of college-educated in the block group. Even controlling for own ideology, an increase of 0.1 in the fraction of liberals (Democrats, Greens, or Peace and Freedom) reduces consumption by 1.0 percent.[17] Controlling for neighborhood ideology reduces, by a small amount, the size of the coefficients on the interaction of treatment with own ideology. College graduates are no more likely than non-college graduates to change their consumption in response to the treatment but those living in a census block group with a higher fraction of college graduates are more likely to reduce their consumption.

The last regression controls for the effect of house characteristics on treatment response. Those in older houses, in bigger homes, and in electric homes reduce their consumption more. Housing characteristics may reflect occupant characteristics. Liberals are more likely to be in older houses (but less likely to be in bigger homes). Unregistered voters are more likely to be in electric homes and in smaller homes. Controlling for housing characteristics, relative to conservatives, liberals reduce their consumption by 0.8 percent and each increase of 0.1 in the fraction of liberals in the census block group reduces consumption by 0.7 percent.

Treatment effects estimated from the sixth regression in Table 3 are positive for roughly a fifth of the sample (see Figure 1). These treated households who increase their consumption are on average increasing their daily usage by 0.34 kwH from a baseline usage of 30.79 kWh per

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[17] We experimented with a quadratic in the fraction of liberals but found no evidence of non-linear effects.

day. Facing an increasing block tariff pricing scheme, at Tier 2 summer rates, they are paying an extra $2 per month for increasing their consumption. Treatment effects are positive for 41% of conservatives compared to 19% of liberals. Treatment effects are positive for only 6% of liberals who purchase energy from renewable resources and who donate to environmental causes.

When we restricted the sample to households whose electricity usage was above the median in 2006 (precisely those households a utility would want to target to reduce total electricity demand), we obtained a similar response for liberals but a larger response for households who pay for renewable energy (see Table 4). The effects of being in an older home and in an electric home are no longer as large and each doubling of household square footage increases the treatment effect by 1.8 percent.

Table 5 examines the role that environmental ideology plays in responding to receiving the HER. We use the regression results from Table 3's column (4) and Table 4's column (4). Evaluating all characteristics at the median, the treatment effect for liberals who purchase energy from renewable resources, who donate to environmental causes, and who live in a block group where the share of liberals is at least in the 75th percentile (less than 1 percent of our sample) is -0.031. The treatment effect for registered liberal who live in a block group where the share of liberals is at least in the 75th percentile (26% of our sample) is -0.011. The treatment effect for a conservative who does not pay for renewable energy, does not donate to environmental groups, and is in bottom 25th percentile liberal block group (22 percent of our sample) is 0.007. If this type of conservative (does not pay for renewable energy, does not donate to environmental groups, and is in the bottom 25th percentile liberal block group) consumed above the median in 2006 (13 percent of our sample), the treatment effect is not statistically distinguishable from 0.

The treatment effect becomes -0.055 for a liberal who consumed above the median in 2006 and who purchases energy from renewable resources, who donates to environmental causes, and who lives in a block group where the share of liberals is at least in the 75th percentile. It is -0.025 for a liberal who consumes above the median in 2006 and who lives in a block group where the share of liberals is at least in the 75th percentile (12% of our sample).

Our examination of seasonal patterns of response to the treatment leads us to conclude that liberals are more likely to turn down the air-conditioning in the summer in response to the treatment. When we added to Equation 6 in Table 3 an interaction between treatment and summer months (May 1-October 31) and an interaction between treatment, summer months, and liberal, we obtained a coefficient on the interaction between treatment and summer months of 0.003 ($\hat{\sigma}$=0.002) and a coefficient on the interaction between treatment and summer months and liberal of -0.032 ($\hat{\sigma}$=0.002). When we examined households living in electric homes (results not shown), we found that these households mainly adjusted in the summer but they also adjusted in the cooler months (March, April, October, and November). They did not adjust in the coldest months (December, January, and February).

It is theoretically ambiguous whether the HER reports will have a larger impact in the short run or the medium term. When a household first receives such a report this may be a salient event whose "new news" shocks the household and subsequent reports reinforce the original news. In this case, we might observe a large drop in consumption followed by a constant level (climate adjusted).

Alternatively, in the medium term a household is more likely to adjust more of its durables stock and may make more energy efficient investments when it makes new investments in such durables.[18] The evidence suggests that this strategy is being pursued. We found that households in the treatment group were more likely to obtain a rebate from the utility for purchasing an energy efficient durable. In a probit regression (results not shown) of the probability of obtaining a rebate on whether the household was in the treatment group, the household's political affiliation, the age of the household head, and the household's baseline electricity usage, we found that the derivative of the coefficient on the treatment dummy was a statistically significant 0.006 ($\hat{\sigma}$=0.002). At the sample mean of 0.056, this represents an 11 percent increase in the probability of obtaining a rebate.

Opting out of the Treatment

The decision to quit the HER treatment and consumer survey reactions to the HER report provide additional evidence on which subgroups of the population disliked the treatment that are consistent with our identity story. Households that opted out of the treatment were more likely to be high electricity consumers, both relative to their neighbors and in absolute levels, and they were less likely to be liberals than conservatives (see Table 6). At the mean opt out rate of 0.020, a liberal was 15% percent less likely to opt out. In a subsample of consumers interviewed about the home energy reports, high electricity users were more likely to claim that the reports were useless or that they disliked them. Liberals were less likely than conservatives to state that the reports were useless or that they disliked them. Being liberal decreased the probability of finding a report useless by 0.131, a decrease of 44% from the sample mean of 0.301. Being a liberal decreased the probability of disliking the report by 0.102, a decrease of

[18] We also examined the persistence of the treatment effect. We found that in 2009 positive treatment effects among low using Republicans become smaller relative to 2008, but we found no differential effects for liberals.

28% from the sample mean of 0.363. Liberals and conservatives did not report differential rates of spending less than 2 minutes reading the report (results not shown).

Conclusion

"Nudge" based policy prescriptions seek to make us healthier, richer in our retirement (through opt out defaults), and better environmental citizens. In one consumer finance experiment, "nudges" that are inexpensive to implement are as effective as large relative price changes (Bertrand et al. 2010).

We have shown that while energy conservation "nudges" work with liberals, they backfire with some conservatives. Energy conservation and efficiency have become liberal identifiers. Greens may reduce their consumption in response to the receipt of a Home Energy Report because both private and social effects work in the same direction. They want to be good global citizens and suffer when they are made aware that they are "part of the problem." The knowledge that their absolute and relative levels of consumption are known to the electric utility may only reinforce the desire to reduce consumption. In contrast, non-greens not only may feel no desire to engage in voluntary restraint, but, aware that they are being watched, may increase their consumption to tweak the authority's nose. Individual, political commentary, and party positions on environmental issues have become more extreme over the last quarter of a century (Dunlap, Xiao, and McCright 2001) and this may re-enforce differential behavioral responses. List (2007) highlights in an experimental setting how households signal their types through the actions they take.

These "defiers" pose a challenge for the design of public policies intended to mitigate social externalities. To design nudges effectively, a "nudger" must anticipate how diverse subjects will respond. What works on average in this California county may not work on average in Lubbock, Texas if the proportion of greens is less in Lubbock. Messages need to be targeted to particular ideological groups, as learned by politicians who have strategically adopted extremism to induce their supporters to show up to the polls (Glaeser, Ponzetto, and Shapiro 2005).

Energy conservation "nudges" may need to be combined with more traditional, but perhaps more politically costly, policies such as strict building code prices and higher prices. Building codes have been effective in reducing electricity consumption by around 15 percent (Aroonruengsawat and Auffhammer 2009; Costa and Kahn 2010; Jacobson and Kotchen 2009) and higher electricity prices both in the short term and through a long run impact on durables choice would reduce consumption.[19]

[19] Recent estimates of price elasticities are -0.39 (Reiss and White 2005) and -0.22 (Borenstein 2009).

Appendix A: Sample Home Electricity Report

[redacted]

Account number: 594860

Home electricity report
bill period: 07/14/07 - 08/13/07

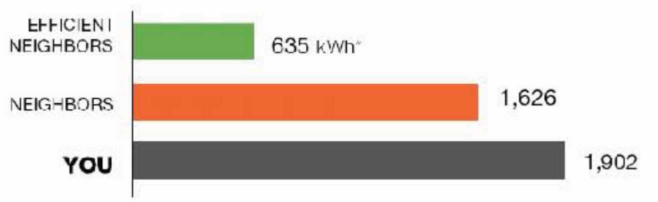
Adam Smith
1400 45th St.
[redacted]

This home energy report is intended to help you understand and make choices about your electricity usage and costs. Each month you will see:

- A comparison of your use to your neighbors
- A comparison to your own use last year
- Personalized tips for reducing your cost

We hope this helps you manage your home electricity use!

Last Month Neighborhood Comparison | You used **17% MORE** electricity than your neighbors last month.

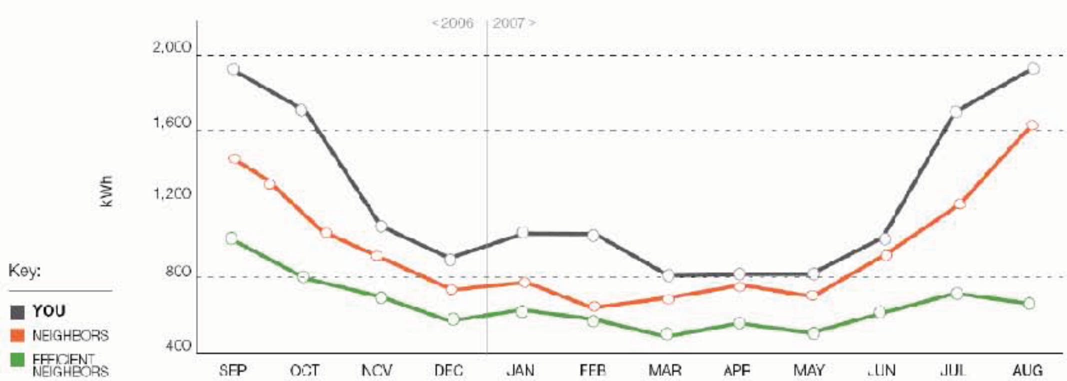


HOW YOU'RE DOING:

GREAT ☺☺
GOOD ☺
▶ **ROOM TO IMPROVE**

*A 100-Watt bulb left on for 10 hours uses 1 kilowatt-hour (kWh).

12 Month Neighborhood Comparison | In the last 12 months you used **32% MORE** electricity than your neighbors. This cost you $645.



WHO ARE YOUR "NEIGHBORS"? We're comparing your usage to 100 homes nearby and similar in size to yours (average 2340 square feet). Your most efficient neighbors are the top 20 in terms of energy efficiency.

Personalized
Action Steps

- ☐ Change your A/C filter
- ☐ Upgrade to efficient A/C
- ☐ Install solar panels

TURN OVER TO LEARN MORE ➡

Source: Residential Energy Use Behavior Change Pilot, OPOWER white paper, http://www.opower.com/LinkClick.aspx?fileticket=cLLj7p8LwGU%3d&tabid=76

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Table 1: Summary Statistics, All Homeowners, Control and Treatment Group

	All Home Owners		Control Group		Treatment Group	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Avg. Daily Electricity (kWh)	27.930	17.710	31.051	15.473	30.801	14.727
Household Size	2.111	1.159	2.111	1.136	2.103	1.137
Age of Head	56.582	14.967	56.941	14.952	56.594	15.085
Household Income	66484.710	43252.980	74826.920	41364.310	74312.590	41546.760
Home Square Footage	1709.447	682.612	1720.876	602.086	1706.109	578.296
Home Year Built	1976.764	20.619	1971.176	18.377	1972.618	18.547
Block Group % College	0.283	0.162	0.364	0.158	0.363	0.162
Block Group % Liberal	0.460	0.105	0.436	0.098	0.438	0.097
Registered as						
Republican, American, Libertarian	0.412	0.492	0.447	0.497	0.438	0.496
Democrat, Green, Peace and Freedom	0.461	0.498	0.439	0.496	0.449	0.497
No party	0.124	0.330	0.112	0.316	0.112	0.315
Other	0.002	0.045	0.002	0.046	0.002	0.043
Not registered	0.474	0.499	0.425	0.494	0.430	0.495
College Educated	0.355	0.479	0.411	0.492	0.406	0.491
Donates to Environmental Causes	0.082	0.275	0.099	0.299	0.097	0.296
Electric Home	0.165	0.371	0.246	0.431	0.264	0.441
Pays for Renewable Energy	0.088	0.283	0.104	0.305	0.103	0.304
Observations	285,717		48,058		33,664	

Note: All variables listed after the block group variables are dummy variables.

Table 2: Summary Statistics by Political Party Registration

	Conservatives		Liberals	
	Mean	S.D.	Mean	S.D.
Fraction in Treatment Group	0.406	0.491	0.416	0.493
Avg. Daily Electricity (kWh)	33.952	16.236	29.551	14.248
Household Size	2.352	1.192	2.096	1.099
Age of Head	58.490	14.104	59.199	13.413
Household Income	84279.550	43711.440	74806.960	40377.220
Home Square Footage	1828.034	632.129	1672.423	548.087
Home Year Built	1973.234	16.881	1968.815	19.375
Block Group % College	0.380	0.157	0.375	0.156
Block Group % Liberal	0.408	0.086	0.454	0.101
College Educated	0.419	0.493	0.403	0.490
Donates to Environmental Causes	0.087	0.282	0.114	0.318
Electric Home	0.247	0.431	0.237	0.425
Pays for Renewable Energy	0.070	0.256	0.141	0.348
Observations	21,193		21,172	

Note: A conservative is defined as Republican, American Party, or Libertarian. A liberal is defined as Democrat, Green, or Peace and Freedom.

Table 3: Treatment Effects by Ideology, Education, and Structure

	Dependent Variable: Log(Mean Daily kWh)			
	(1)	(2)	(3)	(4)
Treated	-0.021***	-0.004*	0.059***	0.213***
	(0.002)	(0.002)	(0.006)	(0.040)
Treated x				
(Registered conservative)				
(Registered liberal)		-0.011***	-0.007***	-0.008***
		(0.003)	(0.003)	(0.003)
(Registered other party)		0.023	0.019	0.019
		(0.026)	(0.025)	(0.026)
(No registered party)		0.002	0.003	0.003
		(0.004)	(0.004)	(0.004)
(Not in voter registration data)		-0.029***	-0.027***	-0.028***
		(0.003)	(0.003)	(0.003)
(Donates to environmental organizations)		-0.010***	-0.011***	-0.009**
		(0.004)	(0.004)	(0.004)
(Pays for renewable energy)		-0.015***	-0.011***	-0.010**
		(0.004)	(0.004)	(0.004)
(College graduate)			0.004	0.004
			(0.003)	(0.003)
(Liberal share within block group)			-0.096***	-0.071***
			(0.013)	(0.014)
(College graduate share within block group)			-0.067***	-0.058***
			(0.008)	(0.008)
(Logarithm of age of house)				-0.017***
				(0.003)
(Logarithm of square footage of house)				-0.014***
				(0.005)
(Electric House)				-0.028***
				(0.003)
Household fixed effects	Y	Y	Y	Y
Month-Year fixed effects	Y	Y	Y	Y
Observations	2,760,175	2,760,175	2,760,175	2,760,141
R-squared	0.804	0.804	0.804	0.804

Note: Each observation is a household-billing cycle. Standard errors, clustered on the household, are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Additional control variables are a cubic in mean daily (24 hr.) temperature, the cubic in daily temperature interacted with a dummy indicating whether the home is an electric home, household fixed effects, and year-month fixed effects. Mean daily kWh are 31.69. Conservative is defined as Republican, American Party, or Libertarian. Liberal is defined as Democrat, Green Party, or Peace and Freedom.

Table 4: Treatment Effects by Ideology, Education, and Structure among Heavy Users

	Dependent Variable: Log(Mean Daily kWh)			
	(1)	(2)	(3)	(4)
Treated	-0.025***	-0.005*	0.063***	-0.105*
	(0.002)	(0.003)	(0.009)	(0.054)
Treated x				
(Registered conservative)				
(Registered liberal)		-0.015***	-0.010***	-0.009***
		(0.003)	(0.003)	(0.003)
(Registered other party)		0.031	0.028	0.029
		(0.035)	(0.034)	(0.035)
(No registered party)		-0.004	-0.003	-0.002
		(0.005)	(0.005)	(0.005)
(Not in voter registration data)		-0.037***	-0.032***	-0.031***
		(0.004)	(0.004)	(0.004)
(Donates to environmental organizations)		-0.010*	-0.012**	-0.010**
		(0.005)	(0.005)	(0.005)
(Pays for renewable energy)		-0.023***	-0.020***	-0.019***
		(0.006)	(0.006)	(0.006)
(College graduate)			0.010***	0.008**
			(0.003)	(0.003)
(Liberal share within block group)			-0.122***	-0.077***
			(0.018)	(0.020)
(College graduate share within block group)			-0.062***	-0.086***
			(0.010)	(0.011)
(Logarithm of age of house)				-0.010***
				(0.003)
(Logarithm of square footage of house)				0.026***
				(0.007)
(Electric House)				-0.013***
				(0.003)
Household fixed effects	Y	Y	Y	Y
Month-Year fixed effects	Y	Y	Y	Y
Observations	1,379,727	1,379,727	1,379,727	1,379,727
R-squared	0.675	0.675	0.675	0.675

Note: The sample is restricted to households consuming above the median mean daily kWh in 2006. Each observation is a household-billing cycle. Standard errors, clustered on the household, are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. Additional control variables are a cubic in mean daily (24 hr.) temperature, the cubic in daily temperature interacted with a dummy indicating whether the home is an electric home, household fixed effects, and year-month fixed effects. Mean daily kWh are 41.48. Conservative is defined as Republican, American Party, or Libertarian. Liberal is defined as Democrat, Green Party, or Peace and Freedom.

Table 5: Predicted Treatment Effects by Ideology

	Treatment Effect	Std. Err.
Registered liberal, pays for renewable energy, donates to environmental groups, and in top 75th percentile liberal block group	-0.031***	0.000
Registered liberals and in top 75th percentile liberal block group	-0.011***	0.003
Registered conservative, does not pay for renewable energy, does not donate to environmental groups, and in bottom 25th percentile liberal block group	0.007***	0.003
Above median electricity usage in 2006		
Registered liberal, pays for renewable energy, donates to environmental groups, and in top 75th percentile liberal block group	-0.055***	0.003
Registered liberal and in top 75th percentile liberal block group	-0.025***	0.004
Registered conservative, does not pay for renewable energy, does not donate to environmental groups, and in bottom 25th percentile liberal block group	-0.004	0.003

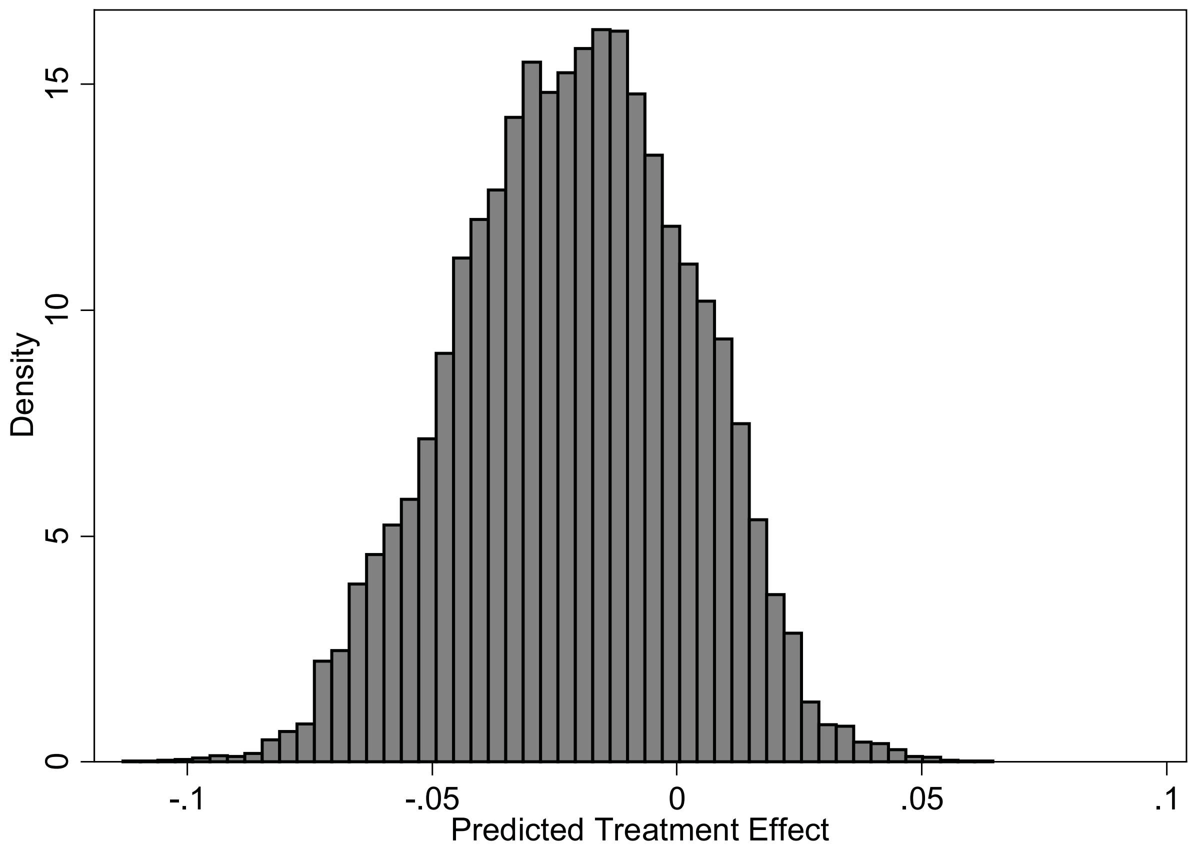
Note: Predicted treatment effects are estimated from Regression 4 in Table 3. *** indicates statistical significance at the 1% level. Everyone in the treatment group is assigned the given characteristics while all other characteristics are kept at their median values. Conservative is defined as Republican, American Party, or Libertarian. Liberal is defined as Democrats, Green Party, and Peace and Freedom.

Table 6: Decision to Opt Out of Treatment and View of Reports by Ideology

	Dependent Variable =1 if		
	Opt Out	Reports of No Value	Dislike Reports
Dummy=1 if			
Above community mean electricity use	0.013***	0.082**	0.138***
	(0.002)	(0.035)	(0.036)
Logarithm of 2006 electricity consumption	0.008***	0.159***	0.103***
	(0.002)	(0.038)	(0.040)
Age of household head	0.000***	0.003***	0.001
	(0.000)	(0.001)	(0.001)
Dummy=1 if registered			
Republican, American Party, Libertarian			
Democrat, Green, Peace and Freedom	-0.003**	-0.131***	-0.102***
	(0.001)	(0.032)	(0.035)
Dummy=1 if not registered	-0.004**	-0.078**	-0.031
	(0.001)	(0.032)	(0.036)
Pseudo R-squared	0.062	0.055	0.04
Observations	32,667	1,061	1,061

Note: The opt out decision is estimated for all treated households. The mean opt out rate is 0.020. A subsample of the treatment group was interviewed about the home energy reports. 30.1% of the sample found the reports to be not at all or not very valuable. 36.3% of the sample reported not liking or being indifferent about receiving the reports. Standard errors are in parentheses.

Figure 1: Predicted Treatment Effects for Every Household in the Treatment Group



Note: Predicted from Regression 4 in Table 3.

Social Norms and Energy Conservation

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Abstract

This paper evaluates a pilot program run by a company called Positive Energy to mail home energy reports that compare a household's energy use to that of its neighbors and provide energy conservation information. Using data from randomized natural field experiment at 80,000 treatment and control households in Minnesota, I estimate that the program reduces energy consumption by 1.9 percent relative to baseline. In a treatment group receiving reports each quarter, the effects appear to decay in the intervening months, suggesting that the reports successfully motivate or remind households to conserve but that this attention or motivation is not durable. I show that "profiling," or using a statistical decision rule to target the program at households whose observable characteristics suggest larger treatment effects, could substantially improve cost effectiveness in future programs. The effects of this program provide additional evidence that non-price "nudges" can substantially affect consumer behavior.

JEL Codes: C93, D12, L51, L94, Q40, Z13.

Keywords: Social norms, household energy conservation, randomized field experiments.

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1 Introduction

Climate change has emerged as one of the most pressing issues of the early 21st century, and energy efficiency could be a principal way of addressing it. Many analysts believe, however, that over the past 35 years energy efficiency has not lived up to its potential to deliver large energy savings at seemingly low cost. One critical opportunity that may be underexploited is insights from behavioral science, including the power of social norms. One critical difficulty has been a lack of consensus on how to measure the causal effects of energy efficiency programs, which has hindered the ability to learn what works and take demonstrably-effective programs to scale.

This paper econometrically evaluates a large-scale energy efficiency program run by a company called Positive Energy for an electric utility in Minnesota. The program involves sending to residential consumers Home Energy Reports with two key features. The first is an Action Steps Module that provides information, specifically targeted to each household, on ways to conserve energy. The second is a Social Comparison Module that details the household's electricity consumption and compares it to that of its one hundred nearest geographical neighbors in houses of comparable square footage. The normative comparison feature was motivated by academic work showing that social comparisons can powerfully affect behavior, including inducing people to conserve energy (Goldstein, Cialdini, and Griskevicius 2008), vote (Gerber and Rogers 2009), or stop littering (Cialdini, Reno, and Kallgren 1990). This literature has developed alongside work by economists on social learning[1] and conditional cooperation in the private provision of public goods[2].

Positive Energy's Home Energy Reports are but one example of a wide variety of energy efficiency programs that utilities operate to satisfy regulatory requirements, including information campaigns, energy audits and weatherization, and rebates for purchasing energy efficient durable goods such as lightbulbs, air conditioners, and water heaters. The causal effects of these programs are typically estimated using the "deemed savings approach": multiply the number of participants by ex-ante "engineering estimates" of the energy savings per participant relative to some counterfactual. While those in industry have long questioned the accuracy and precision of deemed savings and other approaches[3] and are aware of the conceptual usefulness of randomized controlled trials[4], there is no consensus on how the effects of energy efficiency programs should be measured. In this context, one of the remarkable features of the Positive Energy program is that it was implemented as a randomized, controlled experiment, allowing an unbiased estimate of treatment effects in the eligible population.

The effects of Positive Energy's program are of interest for two reasons. First, independent estimates of the reductions driven by the Home Energy Reports are important *per se*. The program has been introduced at utilities serving 15 percent of the U.S. population, in Northern and South-

[1] This literature includes Banerjee (1992), Beshears, *et al*, (2009), Conley and Udry (Forthcoming), Duflo and Saez (2002, 2003), Foster and Rosenzweig (1995), and Mobius, Niehaus, and Rosenblat (2005). In these settings, agents make a choice under uncertainty and draw inference from others' behavior because others may have distinct and useful information.

[2] Recent work on conditional cooperation includes Fischbacher, Gachter, and Fehr (2001, Shang and Croson (2004), Frey and Meier (2004), and Alpizar, Carlsson, and Johansson-Stenman (2008). These studies suggest that people are more likely to contribute to public goods when informed that others are contributing more.

[3] Nadel and Keating (1991) show that there was substantial bias and variance in deemed savings estimates relative to ex-post econometric evaluations.

[4] Energy efficiency programs are rarely evaluated using randomized trials, although the program analyzed by Davis (2008) is one exception. There is, however, a long history of randomized evaluations of energy *pricing* programs, including Aigner (1984), Allcott (2009), Aubin, *et al*, (1995) and Wolak (2006). Indeed, the British Domestic Tariffs Experiment, carried out between 1966 and 1972, was one of the first large-scale social experiments in any domain (Levitt and List 2009).

ern California, Washington, Minnesota, Illinois, Colorado, and Virginia, and it has been covered in the New York Times (Kaufman 2009), the Atlantic (Tsui 2009), National Public Radio, and other popular media outlets. Other utilities are considering adopting the program, and credible documentation of the magnitude of it effects will affect the disposition of millions of dollars in potential investment.

The success or failure of the Positive Energy program is also of more conceptual interest. Whether this program is perceived as successful will influence whether future energy efficiency programs are influenced by findings from behavioral science and evaluated via randomized trials. If the program works, it would be a remarkable illustration of the effectiveness of non-price interventions, in a world where the bulk of spending on energy efficiency programs currently goes to large rebates for household durables (Gillingham, Newell, and Palmer 2006). A successful non-price intervention it would be consistent with a growing empirical literature on how non-price interventions, or "nudges," can substantially affect individuals' behavior, including Bertrand, *et al*, (2010)[5], Benartzi and Thaler (2004), Ashraf, Karlan, and Yin (2006), and others.

The point estimates of the Average Treatment Effect (ATE) of Positive Energy's monthly Home Energy Reports range from a 1.8 to a 2.1 percent reduction in electricity consumption relative to baseline. The 95 percent confidence intervals in the five primary specifications span a range from 1.52 to 2.50 percent. Because of the large sample size and randomized control group, the estimated ATEs are highly robust to alternative specifications of fixed effects and control variables. The effects do vary somewhat depending on the envelopes in which they are delivered, the time elapsed since the beginning of the treatment, and the season.

Program households were randomly assigned to groups that would receive Reports every month versus every quarter. Interestingly, the Quarterly group treatment effects decay in subsequent months relative to the Monthly group, then increase again with the receipt of a second report, then decay again. The decay is economically significant, as it constitutes half of the treatment effect. Additional survey evidence suggests that this is the result of a cycle in which receiving a letter reminds or motivates the household to conserve, the household tires of the change over time, and motivation or memory is re-instilled upon receiving the next quarter's Report.

Econometric results also show that households that were high energy consumers before the treatment conserve substantially more than households whose baseline consumption was low. As I will discuss, this is consistent with one of the chief concerns in providing information on social norms: while individuals worse than the norm may improve, a "boomerang effect" might cause those better than the norm to regress (Clee and Wicklund 1980, Ringold 2002). More generally, I show that the program has heterogeneous treatment effects, not just as a function of baseline usage, but also correlated with other household characteristics observable to a program designer. This suggests that "profiling," or targeting future treatment toward units with higher expected treatment effects, could improve average efficacy and cost-effectiveness for those treated.

The final section of the paper builds on this insight to develop a statistical treatment rule under

[5] For their study, Bertrand, *et al*, partnered with one of the largest banks in South Africa to offer new loans to existing clients, via letters that varied both the interest rate offer and other psychological cues. They varied the number of different potential loans that were presented (to test whether greater choice could overload decision-making), how the interest rate was compared to some market benchmark, the race and gender of the person in a photo on the offer letter, the expiration date of the offer, whether the offer is combined with a promotional giveaway, and whether the letter mentions suggested uses for the loan. Consistent with economic theory, they found that consumers that had been offered lower interest rates were much more likely to take up the loans. They also found, however, that any one psychological cue could affect takeup by almost as much as a one to two percentage point change in the monthly interest rate. See Allcott and Mullainathan (2009a and 2009b) for further discussion of applications of non-price approaches to energy conservation suggested by recent research in psychology and economics.

which a decisionmaker allocates future treatment to minimize the expected cost of achieving some required aggregate treatment effect, conditional on information from the existing experiment. The routine draws on a recently-growing literature on using the results of randomized experiments to develop statistical decision rules for future treatments, including Berger, Black, and Smith (2000), Dehejia (2005), Graham, Imbens, and Ridder (2009), Hirano and Porter (2006), Imai and Strauss (2009), and Manski (2004, 2009). I show that, if the program were to be administered to only half of the population, profiling would improve cost effectiveness by 80 percent relative to random assignment.

This paper proceeds by providing background on Positive Energy's pilot experiment in Minnesota. Section III details the econometric strategy, Section IV presents results, Section V details the statistical treatment rule and gains from profiling, and Section VI concludes.

2 Experiment Overview

2.1 Motivating Literature

Social scientists have long been aware of the potential for social norms to affect individual behavior. For example, there is a large experimental literature in psychology that shows that providing people with information on social norms can have powerful influence (Cialdini 2003, Goldstein, Cialdini, and Griskevicius 2008, Gerber and Rogers 2009, Cialdini, Reno, and Kallgren 1990). This could occur for a number of reasons. We might emulate the norms of high status people to signal high status (Veblen 1899, Pesendorfer 1995). We might conform to customs due to social penalties for noncompliance (Akerlof 1980). We might follow a subgroup norm to signal horizontal type (Levy 1959, Wernerfelt 1990) or because of intrinsic utility from conforming to an identity (Akerlof and Kranton 2000). We might conform to a norm of prosocial behavior to signal benevolent underlying preferences (Bernheim 1994) or to otherwise receive social acclaim (Becker 1974). Finally, we might follow others because their choices are informative when we have imperfect information (Banerjee 1992). The explanations for conformity depend most importantly on whether the action taken is observed or unobserved and whether we are considering consumption of private goods or private provision of public goods.

There are three pathways through which information on neighbors' electricity consumption would most likely affect a household's quantity of electricity demanded. First, the Reports could induce households to conserve if individuals derive utility from being shown to be more virtuous than their neighbors. Second, because some externalities, primarily from power plant greenhouse gas emissions, are not internalized in electricity prices, many consumers perceive that energy conservation helps provide a public good (more moderate global climate). A literature on "conditional cooperation," including Alpizar, Carlsson, and Johansson-Stenman (2008), Cialdini (2003), Fischbacher, Gachter, and Fehr (2001), Frey and Meier (2004), and Shang and Croson (2004), has shown that people are more likely to contribute to public goods when informed that others are contributing.

Third, the information in the Home Energy Reports may facilitate social learning, as in Conley and Udry (Forthcoming), Duflo and Saez (2002, 2003), Foster and Rosenzweig (1995), Mobius, Niehaus, and Rosenblat (2005), and other applications. Electricity costs the average household about $1000 per year, but households may not be very knowledgeable about the amount of electricity they consume or what factors influence consumption. Given this uncertainty, new information on neighbors' consumption might induce the household to re-optimize around the level of household energy services or the efficiency with which energy input is transformed into energy services. For example, a household that learns that comparable households are using much less energy might infer that they themselves have low-cost opportunities to conserve.

All of these channels suggest that revealing the social norm should affect high consumption households more than low consumption households. Importantly, the second and third channels suggest that learning that they consume less than normal would induce low consumption households to conserve *less*. This has been called the "boomerang effect" (Clee and Wicklund 1980, Ringold 2002). In a pilot study of electricity conservation that influenced the design of Positive Energy's Home Energy Reports, Schultz, Nolan, Cialdini, Goldstein, and Griskevicius (2007) found that revealing the social norm did indeed cause low consumption households to increase consumption. Their solution was to add "injunctive social norms," which label others' behavior as good or bad, along with the "descriptive social norms," which simply describe others' behavior.

There is also a large body of existing work on how information provision and behavioral interventions can induce households to conserve energy. Giving consumers feedback on their consumption, providing information on energy savings opportunities, comparing their use to their neighbors' use, facilitating public or private goal setting, and structuring commitment devices have caused households to reduce energy consumption by 5-20 percent. Abrahamse, et al, (2005), Darby (2006), Fischer (2008), Shippee (1980), and Stern (1992) provide reviews of this literature. Many of these approaches, however, have been tested only in the lab, or in field experiments with small or unrepresentative groups. Furthermore, even if effective in field experiments, many of these academic interventions have been too labor-intensive to be used as a large-scale energy efficiency program.

Positive Energy intentionally designed its pilot programs to exploit this existing body of knowledge. While the randomization into treatment and control will allow an unbiased estimate of the overall effect of the Reports, because the entire Treatment group received the social comparisons, historical consumption information, and energy efficiency tips, it will not be possible to determine what aspect of the Reports drives that treatment effect. As in Benartzi and Thaler (2004), I can evaluate the overall efficacy of the program motivated by behavioral science, but I cannot test more refined hypotheses about the channels through which the program works. Although popular media outlets have concluded it is the peer comparison feedback in particular that reduces households' electricity usage, the treatment arms of the pilot program itself provide no evidence that this is actually true. What's interesting about the Positive Energy pilot experiments is that they take an existing body of scientific knowledge and implement it at scale.

2.2 Experimental Design

As of summer 2009, Positive Energy has contracts to operate pilot projects for utilities in California, Minnesota, Washington, Illinois, Colorado, and Virginia. This paper evaluates their program at an electric utility called Connexus Energy, which serves customers in seven counties in central Minnesota near Minneapolis and St. Paul[6].

The households eligible for the Connexus Energy pilot experiments were those with a full one year of electricity bill history as of January 2009, as historical consumption data were required to construct the social comparisons. From the 78,492 eligible households, approximately half (39,217) were randomized into a Treatment group, which would receive Home Energy Reports, and the rest

[6] Positive Energy carries out internal statistical evaluations, and independent evaluations of their pilot programs in Puget Sound and Sacramento are carried out by Ayres, Raseman, and Shih (2009) and Violette, Provencher, and Klos (2009).

were randomized into a Control group, which would not. Some utility staff were automatically enrolled in the reports and are therefore excluded from the analysis. The experiments are still ongoing.

The Reports are several-page letters with two key components. The first, which is illustrated in Figure 8.1 and appears at the top of the letter's first page, is the Social Comparison Module. This compares the household's electricity consumption over the past twelve months to the mean of its comparison group and the 20th percentile. In an attempt to address the potential boomerang effect, the "Efficiency Standing" on the right side of the Social Comparison Module adds injunctive messages: it labels low- and moderate-consumption households as "Great" and "Good" and adds "smiley face" emoticons.

The Report's second key component is the Action Steps Module. As illustrated in Figure 8.2, this suggests both changes to the household's stock of energy-using durable goods and to the use of that capital stock. These suggestions are targeted to different households based on historical energy use patterns and demographic characteristics. For example, households whose energy use was relatively high the previous summer were more likely to receive suggestions to purchase new energy efficient air conditioners.

The mechanics of the billing and report mailing process are as follows. The utility sends a worker to read each household's electricity meter approximately once per month, records the consumption over the period, and sends the consumer its monthly bill. Meanwhile, the meter readings are sent electronically to Positive Energy, where each household's social comparison is computed. The Home Energy Report is printed by an outside contractor, send via U.S. Mail, and at some point is opened at the household. The time between meter reading and the arrival of the Report is typically about three weeks. For almost all households, the first round of Reports were constructed after each household's meter reading in January 2009, although a small handful of households were randomized into Treatment and Control groups over the next few months. Sixty percent of Treatment group households were randomly assigned to receive the letters after every monthly meter reading, while 40 percent received them only once a quarter[7].

2.3 Data and Baseline Characteristics

I observe the 1.5 million electricity bills for all Treatment and Control households between January 2008 and August 2009, including the date of meter reading and consumption between that reading and the previous. I also observe Positive Energy's social comparison information for every household, including whether they were rated as "Below Average," "Good," or "Great," and how far they were from the cutoffs to be in each of the other categories. I observe both the social comparisons that the Treatment group did receive and what the Control group would have received. For each billing period, I also observe the number of Heating Degree-Days or Cooling Degree-Days, which are correlated with the amount of electricity that should be required to keep a house at a

[7] Two other variations in the treatment should be noted. After the second Report, the normative messaging was made more "Gentle" for a randomly selected half of the Treatment group. In the "Gentle" condition, the "Below Average" efficiency group no longer saw that there were "Great" and "Good" categories; they instead simply see the message that "You used more than average - Turn the report over to find ways to save." Positive Energy also experimented with sending different envelope types. Because the different envelope types and "Gentle" treatment do not have sharp economic interpretation, and because the estimated effects of these treatments are not substantially different, the treatment effects presented in this paper combine the different envelopes and the Gentle and non-Gentle treatments into one Average Treatment Effect.

comfortable temperature[8].

Table 7.1 displays the baseline observable characteristics for the Treatment and Control group. Baseline Usage, which is the average across all meter reads in 2008, is 29.7 kilowatt-hours per day for both the Treatment and Control groups. For households ever in the "Great," "Good," or "Below Average" groups, average Baseline Usage is 16.5, 25.0, and 40.7 kilowatt-hours per day, respectively. Although the household sizes are similar by construction, the "Great" group is poorer, has fewer household members, and has houses that are worth less.

For context, consider that a medium-sized (75 watt) lightbulb used four hours each day consumes 0.3 kilowatt-hours. A typical window air conditioner running at its highest setting for five hours uses 5 kilowatt-hours. As illustrated in Figure 8.3, heating and cooling are the primary uses of household electricity in the United States: over half of annual electricity consumption is for refrigerators, air conditioners, and space and water heating. In the most recent available data, computers, televisions, and lighting combined account for only 15 percent of electricity use (US Energy Information Administration 2001).

Connexus has provided demographic data for each account number in the dataset[9], including characteristics of the house (Age, an indicator for Gas Heat, Value, an indicator for Rental, Single Family, and Square Footage) and of the occupants (Age of household head, Household Size, and Income). On Baseline Usage, as well as on all other observable characteristics, the Treatment and Control groups are strikingly well-balanced. One of the ten baseline characteristics, the age of the head of household, is statistically different with 90% confidence; the Treatment and Control averages differ by less than 0.2 years. As would be expected in a randomized experiment, an F test fails to reject that the two groups are identical on observables.

2.4 Attrition

The pilot program experienced two forms of attrition, account closure and opting out. Consumers close accounts when they move to a different house; 1.25 and 1.24 percent of Treatment and Control households, respectively, close accounts during the first six months of 2009. Households that close accounts tend to be younger, use less electricity, and have lower incomes, but are statistically indistinguishable on other observed characteristics. There is no statistical difference between the Treatment and Control groups in either the rate of account closure or the correlations between account closure and observable characteristics. The accounts that closed after Treatment began are included in the base specifications during the period when their consumption is observed, although excluding them has no discernible influence on the results.

The second form of attrition is by households that asked to opt out of receiving the Home Energy Reports. In the first six months of 2009, 247 households (0.6 percent of the Treatment group) opted out, likely because they perceived the reports as undesired junk mail. These consumers are statistically different: they are slightly older, have lower incomes, use less electricity, and are less likely to live in single family homes. Although they opted out of receiving Reports, their electricity bills are still observed.

[8] More precisely, Heating Degree-Days is the sum, over all of the days in the billing period, of the maximum of zero and the difference between the day's average temperature and 65 degrees. A day with average temperature 95 has 30 HDDs, while a day with average temperature 60 has zero HDDs. Cooling Degree-Days is the sum, over all the days in the billing period, of the maximum of zero and the difference between 65 degrees and the day's average temperature. A day with average temperature 95 has zero CDDs, while a day with average temperature 60 has five CDDs.

[9] Any missing observations were imputed using conditional mean imputation.

3 Empirical Strategy

3.1 Average Treatment Effects

This section details the straightforward approach to estimate the Population Average Treatment Effect of the Home Energy Reports in the population of eligible households. Simply put, the preferred specification will estimate energy consumption as a function of whether the household is assigned to treatment, conditional on other controls, after removing household fixed effects.

To arrive at that specification, I begin with the standard Rubin Causal Model (Rubin 1974, Imbens and Wooldridge 2009). Each household i has two *potential outcomes* for the energy consumption outcome for the meter read t: one if it were assigned to the Treatment group ($T_i = 1$) and one if it were assigned to the Control ($T_i = 0$). Of course, only one of those outcomes can actually be observed:

$$Y_{it} = Y_{it}(T_i) = Y_{it}(0)(1 - T_i) + Y_{it}(1)(T_i) = \left\{ \begin{array}{ll} Y_{it}(0) & \text{if } T_i = 0 \\ Y_{it}(1) & \text{if } T_i = 1 \end{array} \right\} \tag{1}$$

The quantity of interest is the Average Treatment Effect, $\tau = E[Y_{it}(1) - Y_{it}(0)]$. The "treatment" here is defined as "being mailed the Home Energy Reports or actively opting out." As discussed above, some Treatment households opted out, so the treatment is not simply "being mailed the Home Energy Reports." An alternative potential estimand would be the Intent-to-Treat (ITT) Effect of being sent the Report, for the population that did not opt out; this is simply my ATE divided by the fraction of the population that did not opt out. Since that fraction is very close to 1, the ATE and ITT Effect differ only by a negligible amount. The treatment is also not "opening Home Energy Reports." It is difficult to measure letter open rates, and thus it would be difficult to estimate that second form of ITT Effect.

From a policy perspective, the treatment effect as I define it is the most useful estimand. Positive Energy, and the utilities that contract with them and policymakers that regulate them, want to know the aggregate electricity conservation possible from applying the program to a population. For the population from which the experimental households were drawn, this quantity of interest can be derived simply by multiplying the ATE by the population size[10].

Each household has a different meter reading schedule. Let $t \in \{t_{\min}, ..., t_{\max}\} = \{-12, -11, ..., 0, 1, 2, ...\}$ index bill numbers beginning one year before the treatment began; for each household, each bill number is associated with a particular day, month, and year. Most of the first set of Reports were sent in mid-January, immediately after a meter read at time t_{i0}. As I will show, little substantive or statistical effect is observed until the second meter reading after the January round. All meter reads t more than 40 days after t_{i0}, which for nearly all households is simply the second subsequent monthly meter read, are therefore considered "post-treatment."

The variable P_{it} is a post-treatment indicator variable for household i's meter reading at date t. Denote by Y_{it} the average daily electricity consumption for period ending at t. So that this can later be interpreted as a percentage change, the variable is normalized by control group consumption in the post-period. The variable Q_i denotes whether household i was assigned to the Quarterly group, in either Treatment or Control state. Random assignment to Treatment and Control implies that unobservable factors ε_{it} that influence electricity consumption are uncorrelated with T and Q.

[10] To determine cost-effectiveness, the cost estimates must be adjusted to account for the fact that some households will opt out.

This allows an unbiased estimate of the ATE for both the Monthly and Quarterly Groups with the following equation:

$$Y_{it} = (\tau + \tau_Q Q_i) \cdot T_i P_{it} + (\beta_1 + \beta_2 Q_i) \cdot P_{it} + \mu_{my} + \upsilon_i + \varepsilon_{it} \quad (2)$$

This specification includes month-by-year dummy variables μ_{my} and household fixed effects υ_i; alternative arrangements of fixed effects and controls will also be presented. This is estimated in OLS using the standard fixed effects estimator, using Huber-White ("robust") standard errors, clustered by household. As discussed by Bertrand, Duflo, and Mullainathan (2004), these standard errors are consistent in the presence of any correlation pattern in the errors ε_{it} within household over time.

3.2 Quarterly Group Effects Over Time

After estimating the Average Treatment Effects, I move to an empirical test of whether these effects decay in the Quarterly group over the three bills observed in each quarter. Intuitively, we would like to test whether the Quarterly group conserves more on the first and second bills after receiving a Report (the second and third bills after the one on which the report was based) compared to on the third bill of the quarter. This must control for bill-to-bill (i.e. month-to-month) variation in the average treatment effect, which could be driven by seasonal weather changes. I estimate the following equation:

$$\begin{aligned} Y_{it} = Q_i \cdot \{T_i P_{it} \cdot (\tau_Q + \tau_{Q12} B_{12it}) + P_{it} \cdot (\beta_1 + \beta_2 B_{12it})\} \\ + \sum_{b=t_{\min}}^{t_{\max}} 1(t=b) \cdot \{\beta_{1b} T_i + \beta_{2b}\} + \upsilon_i + \varepsilon_{it} \quad (3) \end{aligned}$$

The variable B_{12it} is an indicator for whether bill t is the first or second bill after receiving a Report. The first line compares the treatment effects τ_{Q12} in the Quarterly group when $B_{12it} = 1$ to the baseline quarterly treatment effect τ_Q. If the treatment effects decay, τ_{Q12} will be more strongly negative than τ_Q. The second line of the equation controls for underlying treatment effects and consumption levels for each bill number, ranging from $t_{\min} = -12$ at the beginning of the data to the most recent bill observation $t_{\max}$.

4 Results

4.1 Treatment Effects

Table 7.2 presents the estimates of the Average Treatment Effect in the eligible population. The top row is the ATE for the Monthly group, while the second row is the difference between that and the Quarterly group ATE. The five specifications include different configurations of fixed effects, month-by-year dummies, and weather controls; number III is the exact specification detailed in the Empirical Strategy section. The point estimates of ATEs center around negative 1.9 percent (Monthly) and 1.1 percent (Quarterly) and are not statistically different between the five specifications.

Table 7.3 displays two alternative approaches to evaluating these pilot programs, motivated by the fact that some in industry are unfamiliar with randomized evaluations and with the natural log function. The first two columns disregard the Control group and use a difference estimator to estimate the treatment effect. The first column is a simple before-after comparison, without accounting for weather or season, and the results are not encouraging: $\widehat{\tau}$ differs from the experimental estimate by almost an order of magnitude. After including fifth-order polynomials in Heating and Cooling Degree-Days and 12 month-of-year dummies in the second column, however, we have an estimated treatment effect that is statistically indistinguishable from and substantively similar to the experimental estimate. Although these specifications were initially included to demonstrate the importance of implementing the program as a randomized trial, it appears that in this particular case, the ATE could have been estimated even in the absence of a control group.

The third specification in Table 7.3 replicates Specification III from Table 7.2, except after logging the dependent variable. In principle, both coefficients are interpreted as percents and should be comparable. In practice, the estimated Monthly (and Quarterly) ATEs in the preferred specification are 42 (and 34) percent higher than that from the log specification. This difference is both substantively significant, in that it would make a noticeable difference in the estimated cost effectiveness, and statistically significant. This difference between the percentage ATEs in logs and levels is relatively constant across (unreported) different specifications, and it is not driven by the 307 observations of the dependent variable that are equal to zero.

Intuitively, this difference is driven by Jensen's Inequality. The treatment effect of interest is the average reduction in kilowatt-hours resulting from the program, and the percent changes reported in Table 7.2 are indeed that quantity, normalized by Control group consumption in the post-treatment period. The log specification is fundamentally different: it is the average percent reduction across households, where each household is effectively normalized to its own average (instead of the Control group average) before computing the ATE. It turns out that the percentage treatment effect is larger (in absolute value) for households with higher consumption, and substantially higher for the most consumptive households. Taking the log of the household's consumption, and then taking the average across households, will understate the ATE (in absolute value) relative to taking the average level change across households and then normalizing into a percent. Although this specification was initially included to demonstrate the innocuousness of using logs to compute percent changes, it is clear that in this case, that approach would be misleading.

Figure 8.4 illustrates the estimated Average Treatment Effect on meter reads over time, separately for the households receiving quarterly and monthly reports. The omitted meter read, number zero, is January for almost all households, the meter reading t_{i0} upon which the first reports were based. For the 12 reads before that, the treatment and control group consumption levels are substantively and statistically identical. This is still the case on the first meter read after t_{i0}. By the second meter read, however, there is a noticeable Average Treatment Effect. That affect grew between February and July, perhaps both because the response to the Reports grows in the early phases of the program and because the effects are stronger in the summer months.

Although the standard errors are wide, the figure suggests that the Quarterly group's ATE is higher in month 2, the first meter read where we would expect to see effects from a Report generated from the month 0 meter read, and then decays in months 3 and 4. A second quarterly report was generated from meter read number 3, and the Quarterly group's treatment effect again increases (in absolute value) in months 5 and 6.

Table 7.4 presents the formal econometric test, described in the Empirical Strategy section, of whether the effects are stronger for meter reads 2, 3, 5, and 6 relative to number 4. Specification I includes separate dummies for the first (and second) bill after receiving the report, which on the graph are reads 2 and 5 (and 3 and 6) respectively. The point estimate ATE for the first bill after receiving a Report is stronger than the point estimate for the second, although this difference is not close to statistically significant. Specification II is identical to Specification I except that it combines the dummy variables for the first and second bills. Both specifications show that the ATEs for the first and second bills after receiving a Report are stronger than the baseline Quarterly ATE, which captures the effect in the third bill of the quarter, with approximately 90 percent confidence in this two-sided test.

Three factors could explain this result. First, the information contained in the Reports - or gathered in response to the Reports - has value that varies by season. Positive Energy targets a set of between 100 and 200 tips to households, and while some have effects that would vary negligibly by season ("Buy an energy efficient refrigerator"), others are fundamentally seasonal ("Replace your heater" or "Cover your pool"). Second, perceiving oneself as a "frugal" consumer of energy could enter consumers' utility functions directly, and the marginal utility of conservation could depend on how recently a Report arrived. Third, the Reports could remind households of opportunities that they already knew about to conserve energy, and that reminder effect could decay over time. The second two channels would be similar to the "Two Steps Forward, One Step Back" story in consumer credit, where fees remind consumers to avoid triggering fees in the future, but that reminder effect decays over months (Agarwal, Driscoll, Gabaix, and Laibson 2006).

Positive Energy has collected surveys of its treatment group that provide some further evidence on this issue. Treatment group households in one of their other pilot programs were asked to self report what behaviors they had changed as a result of receiving the Home Energy Reports. Some of the changes were seasonal changes to household capital stock: weather stripping windows, improving insulation, servicing the air conditioner. Many of the most frequently reported changes, however, were habitual: turning off lights, unplugging electronics, adjusting thermostats, and closing drapes. The more likely it is that these all-season behavioral changes underlie the treatment effects, the more likely it is that the decays in the Quarterly group ATEs are part of a cycle in which the Reports remind or motivate households to conserve, and this attention or motivation decays over months.

Figure 8.5 illustrates the treatment effects by deciles of the distribution of baseline usage, again normalized by Control group average consumption in the post-treatment period. These effects range from less than 0.5 percent for the bottom two deciles of baseline usage to 6.2 percent in the top ten percent. In general, the more electricity a household used before the treatment, the more that it conserved post-treatment. This could be because the most consumptive households had low-cost energy conservation opportunities, and the tips contained in the Reports made them aware of this. This result is also consistent with the idea that previously low-consumption households might not conserve more - or might even conserve less - after receiving information that they are less consumptive than their peers.

4.2 Regression Discontinuity

Some readers may have noticed that the design of the normative categorizations could allow the use of a Regression Discontinuity design to estimate their causal relative effects. Those households just below the cutoff between being categorized "Good" and "Great" are in the limit identical to those households just above, but they received different normative categorizations. This provides a natural experiment that could allow the estimation of the relative effects, for households near the cutoff, of being in the three different categorizations. These effects should be observed two meter reads after the meter read upon which the categorization was based.

In keeping with the tradition of graphical analysis of RD designs (Lee and Lemieux 2009, Imbens and Wooldridge 2009), Figure 8.6 illustrates the treatment group's consumption as a function of distance from the household-specific comparison group's mean consumption, which is the cutoff between being categorized as "Good" vs. "Below Average." The Usage variable on the y-axis, which as before is normalized by Control group post-treatment consumption, is residual of degree-day polynomials and month-by-year controls, but not of household fixed effects, so those households that consume less compared to their peers also tend to have lower residual usage on future bills. Figure 8.7 is the analogous illustration near the 20th percentile of the household-specific comparison group, which is the cutoff between being categorized as "Great" vs. "Good."

What's apparent from both graphs is that the two-sided 95 percent confidence interval around any estimated effects at this bandwidth is approximately four percent - more than double the overall ATE from the Reports. Any differences in ATEs from being placed in one or the other normative category, however, would likely be much smaller. I attempted the RD estimation including household fixed effects and other controls to reduce residual variance, and also added data from one of Positive Energy's other pilot programs. This does not sufficiently reduce the variance around the estimated RD treatment effect to estimate a statistically significant effect of the categorizations or to compute a "tightly-estimated zero" by rejecting reasonably small hypothesized effects.

5 Cost Effectiveness and Profiling

Regardless of the mechanism that drives the variation in treatment effects across households with different baseline usage, the heterogeneity in treatment effects as a function of an observable characteristic suggests that there could be substantial gains from targeting the program towards the most responsive households. Furthermore, because we observe a larger set of household characteristics that might be correlated with the treatment effect, a more comprehensive approach to "profiling" could be useful. My approach builds on the literature detailing the use of existing information on heterogeneous treatment effects to allocate future treatments. This literature dates to Wald's (1950) work on statistical decision theory and has grown recently with work by Berger, Black, and Smith (2000), Dehejia (2005), Graham, Imbens, and Ridder (2009), Hirano and Porter (2006), Imai and Strauss (2009), and Manski (2004, 2009).

Compared to much of the recent literature, this problem is straightforward, as the objective function will be unambiguous and the decisionmaker can be modeled as risk-neutral. As discussed in the introduction, the typical reason why utilities contract with Positive Energy is to help comply with state energy efficiency portfolio standards. I model the decisionmaker as a utility that is trying to minimize its expected cost of compliance with this regulation, which requires a reduction in consumption of S kilowatt-hours from the counterfactual baseline[11]. The key decision variable is which subset of its customer population to assign to Positive Energy treatment.

[11] This requires the simplifying assumption that the regulator allows the utility to comply in expectation as opposed to *ex post*. These regulations often allow the utility to "bank" and "borrow" energy savings across years, meaning that in practice, the utility needs to comply *ex post* only over a long time period.

While we would in principle want to maximize welfare, the utility in practice minimizes cost from its own perspective, with no consideration for the change in consumer welfare. In designing this system, regulators presumably hope that the solutions to the two distinct optimization problems are similar[12]. In practice, and in this analysis in particular, this simplification must be made because while it is easy to observe electricity consumption, it would be quite costly to observe the actions that households take in response to the Reports. It is possible, for example, that the Reports induce some households to buy more energy efficient lightbulbs or appliances. Since the change in treatment group demand for these other goods is unobserved, we cannot compute welfare. This concern is quite general in evaluating energy efficiency programs; one resulting benefit here is that focusing on cost effectiveness keeps this analysis consistent with a previous body of work.

Positive Energy costs the utility a constant amount A per household per year. The utility also has a portfolio of other energy efficiency programs that it knows with certainty will cost C_0 per kilowatt hour, and it sets the size of these programs $K > 0$ in kilowatt-hours saved per year. The decisionmaker has information Θ from the existing large randomized experiment in a representative sample of larger population $\mathcal{P}$.

The decisionmaker seeks a statistical treatment rule $\delta : \mathcal{X} \longrightarrow \{0, 1\}$ that maps individuals with characteristics X to the treated or control states for the Positive Energy program. Denote by Δ the space of possible treatment rules. The scalar $\delta_i = \delta(X_i) \in \{0, 1\}$ is the choice of treatment for individual i with characteristics X_i. The heterogeneous Conditional Average Treatment Effect $\tau(X_i)$ is still typically less than zero, but now consider the units to be in kilowatt-hours per year.

The utility's objective is to minimize C, the expected annual cost of compliance with the regulation:

$$\begin{aligned} \min_{\delta \in \Delta, K} C &= \sum_{i \in \mathcal{P}} \delta_i \cdot A + K \cdot C_0 \\ s.t. \quad E\left[\sum_{i \in \mathcal{P}} -\tau(X_i) \cdot \delta_i | \Theta\right] + K &\geq S \end{aligned}$$

The utility's optimal statistical decision rule collapses to assigning Positive Energy treatment to those households where cost effectiveness is above some threshold value. Given that the cost A is constant across households, this can be written as a constraint on the expected treatment effect:

$$\delta_i^* = 1\left(E\left[-\tau(X_i)|\Theta\right] > R^*\right) = 1\left(-\widehat{\tau(X_i)} \geq R^*\right)$$

$$R^* = \left\{ \begin{array}{ll} \min\{\delta_i^* \tau_i\} & s.t. \ \sum_{i \in \mathcal{P}} \delta_i^* \cdot E\left[-\tau(X_i)|\Theta\right] = S, \quad K^* = 0 \\ & \frac{A}{C_0}, \qquad K^* > 0 \end{array} \right\}$$

[12] One example of why this distinction can be important is the case of rebates for energy efficient appliances. If these rebates are entirely inframarginal (an example of what energy industry analysts call the "free rider problem," not to be confused with the traditional free rider problem in the provision of public goods), their cost effectiveness would be infinite. Given that inframarginal rebates are simply transfers, the efficiency losses would be zero.

The threshold value R^* depends on whether Positive Energy is in the optimum the only program used to satisfy the regulation, or whether other energy efficiency programs are also used and $K^* > 0$. The former case is captured by the second line of the above equation: the utility needs only assign enough households to Positive Energy such that the constraint is satisfied, and there will be some threshold household with lowest cost-effectiveness. The latter case is captured in the third line: if other programs are used, the utility will assign to Treatment all households whose expected cost effectiveness is above the cost effectiveness of the alternative programs.

While recent related applications such as Dehejia (2005) and Imai and Strauss (2009) have used Bayesian estimators to construct a distribution of possible outcomes, I continue with the frequentist approach more familiar to program evaluation in economics. As suggested in the first line of the above equation, I simply use the heterogeneous treatment effects estimated in OLS, $\widehat{\tau_i(X_i)}$ to construct $E[\tau(X_i)|\Theta]$. Mechanically, I then generate that fitted treatment effect for each household, and treatment can be assigned for households above any given R.

5.1 Variable Selection

Estimating $\widehat{\tau_i(X_i)}$ requires the selection of a vector of observables and interactions X to condition on. As discussed in Imai and Strauss (2009), this is a critical decision. Including a large set of controls could allow treatment to be targeted at smaller subgroups that might have particularly large treatment effects. In a finite sample, however, including a larger set of covariates increases the likelihood of overfitting, which could cause the program to be targeted at groups that idiosyncratically appeared to have large treatment effects only in the experimental data.

Imai and Straus (2009) point out that while there is a large literature on how to select "predictive" variables that are correlated with the outcome, there is no consensus on the choice of "prescriptive variables" that help assign units to treatment. Predictive variables are correlated with the outcome, but if they have the same correlation in treatment and control, they are useful for reducing residual variance (improving efficiency), but not for generating a statistical decision rule. Powerful prescriptive variables have two features. First, they are correlated with the treatment effect. Second, they affect the decisions made for each unit.

Future versions of this analysis will use the approach of Zhu, Gunter, and Murphy (2007) to choosing the set of variables to interact with the treatment effect. This version uses three simple covariate specifications, all of which are linear interactions of the treatment effect τ in Equation I with a vector of observable covariates X, such that $\tau = \tau_0 + \tau_X X$. The first specification interacts the treatment indicator variable with all nine available characteristics. The second interacts the treatment indicator only with the three characteristics on which the treatment effect varies with 95 percent confidence in the first specification. The third interaction uses only Baseline Usage.

Table 7.5 presents the results of these specifications. The covariates are normalized to mean zero, standard deviation 1, meaning that a one standard deviation increase in Baseline Usage is associated with an increase in the ATE (in absolute value) of 1.50 to 1.191 percentage points. Houses with gas heat have higher treatment effects in absolute value, while houses with larger square footage have lower treatment effects. No other observable characteristics are statistically significantly associated with the strength of the treatment effect.

5.2 Gains from Profiling

Table 7.6 presents the predicted ATEs for assigning treatment to one half of the population based on the three sets of profiling X variables, compared to assigning to treatment the entire population or a randomly selected sample thereof. These predicted ATEs are computed by re-estimating the treatment effects with the treatment and control observations from the original experiment that now have $\delta = 1$. By this measure, profiling increases the ATE for the treated group by 80%. Interestingly, although the three different sets of X variables assign only 70 percent of units to the same treatment status, the resulting treatment effects on the treated populations are very similar across the three profiling procedures.

The table's second row displays the average annual electricity bill savings for the treated group under the four different assignment mechanisms, based on Connexus Energy's average residential electricity price[13]. The average household saves $15 per year on electricity bills as a result of the changes caused by being sent monthly Home Energy Reports. The table's third row presents the monthly program's cost effectiveness, based on my estimate of the cost per household of administering monthly Reports. The cost effectiveness of the existing randomized program is 5.3 cents per kilowatt-hour saved[14]. This compares very favorably to recent point estimates[15] of the average cost of other utility energy efficiency programs, which range from 4.7 to 13.3 cents per kilowatt-hour (Auffhammer, Blumstein, and Fowlie 2008). Using profiling to target monthly[16] treatment at the most responsive 1/2 of the population improves cost effectiveness by 45 percent, to below 3 cents-kilowatt-hour[17].

6 Conclusion

This paper evaluates the effects of the Positive Energy Home Energy Reports, which give households easily-understandable feedback on past energy consumption, compare them to their neighbors, and provide energy conservation tips. The program is a remarkable departure from traditional energy efficiency programs in that it is designed with direct insight from behavioral science and is implemented using randomized controlled trials. The perceived success or failure of these pilot programs will directly affect millions of dollars of future investment and will more generally influence how future energy efficiency programs are designed and evaluated.

I find that the Average Treatment Effect in the population of eligible Minnesota households is 1.9 percent below baseline. In the group receiving quarterly Reports, his effect decays somewhat

[13] This is available from http://www.connexusenergy.com/resrates.htm.

[14] Note that this cost effectiveness value is different than the number in Allcott and Mullainathan (2009a, 2009b), which is for a large-scale implementation across the country. The appropriate assumptions for baseline electricity demand and program cost differ between the two settings.

[15] I write "point estimate" because there are various forms of uncertainty around this comparison, including not just the statistical uncertainty in the point estimate conditional on the data, but also uncertainties such as regarding the durability of energy savings, the generalizability across different regions, and the quality of the underlying data used to compute the costs of these other programs.

[16] The ATE of the Quarterly reports is much more than 1/3 the ATE of the monthly reports, and depending on Positive Energy's ratio of fixed to variable costs, Quarterly reports could be more cost-effective.

[17] Note that this example is not a reasonable basis for an argument to limit the application of the program: given the low cost of Positive Energy's program, even applying the program households where the treatment effect is smaller than the median can be more cost effective than existing alternative programs. This does, however, show that if the program must be limited to some subset of the population due to budget constraints, there are gains to targeting it towards the most responsive subset.

in the months between Reports, either because the information decays seasonally or because the reminder or motivational effects of a Report decay over time. I also show that the intervention's effects are strongest for households that have highest baseline consumption. This is consistent with (but not causal evidence of) a "boomerang effect" in which learning the social norm can fail to motivate households with low baseline consumption, or even cause them to increase consumption. This is also consistent with the idea that the energy conservation tips in the Reports were more useful for high-consumption households, independent of the social norms.

I then build on the idea of heterogeneous treatment effects to design a statistical decision rule to target the program at households with the highest expected treatment effects. If a utility were limited to implementing the program for half of its residential population, profiling could improve cost-effectiveness by 80%. Even without profiling, the cost effectiveness of the Positive Energy program compares very favorably to traditional energy efficiency programs, which are largely based on expensive subsidies for energy efficient durable goods.

Although the Positive Energy experiment was carried out in a specific domain and requires a general-interest reader to digest some institutional detail, this analysis has two important and generalizable economic implications. First, the analysis adds to a recently-growing appreciation of how "profiling," the targeting of social programs with heterogeneous treatment effects toward individuals with high expected effects, can improve a program's welfare implications. Dehejia (2005) shows that a program that would not be implemented based on examining the ATE alone would optimally be implemented in subgroups with higher Conditional Average Treatment Effects. The Positive Energy example is different in that the intervention is cost effective relative to other energy efficiency programs even in the general population, but I similarly conclude that profiling could substantially increase the intervention's average cost effectiveness.

A second important implication of this analysis is that it adds to recently-growing appreciation of how non-price interventions can affect consumer behavior. Economists in general, and energy efficiency program managers in particular, have historically focused on how prices and subsidies affect demand. The idea that simply being sent a letter in the mail could result in measureable changes in demand is remarkable, especially given that the letters may not have improved consumers' information sets in a relevant way: recall that survey evidence indicates that the bulk of behavioral changes caused by the program are behaviors such as turning off lights that consumers *already knew* could save them energy. From the utility's perspective, interventions such as this are remarkably cheap to implement relative to manipulating prices, and comparable treatment effects therefore implies much better cost effectiveness. Perhaps the most important contribution of this program, therefore, is to provide further evidence that some combination of information, reminders, and social norms can cause substantive changes in consumer behavior at population scale.

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7 Tables

7.1 Baseline Household Characteristics

	Treatment	*Control*	*T-C*	*Great*	*Good*	*Below Av*
Mean: Baseline Usage (kwh/day)	29.74	29.69	0.053	16.52	25.04	40.67
SD (and SE):	(16.44)	(16.17)	(0.117)	(8.05)	(9.68)	(17.89)
Consumer Age	49.98	49.82	0.161	52.57	50.05	48.45
	(12.18)	(12.18)	(0.087)*	(12.99)	(12.34)	(11.38)
1(Gas Heat)	0.92	0.92	-0.0013	0.94	0.93	0.90
	(0.28)	(0.27)	(0.0020)	(0.24)	(0.25)	(0.30)
Household Size	2.61	2.62	-0.010	2.23	2.57	2.84
	(1.22)	(1.23)	(0.009)	(1.07)	(1.18)	(1.28)
House Age	16.27	16.21	0.062	16.56	16.27	16.02
	(6.65)	(6.56)	(0.047)	(6.56)	(6.59)	(6.64)
House Value	393.9	394.7	-0.792	369.6	385.5	414.5
	(139.4)	(139.4)	(0.995)	(121.7)	(132.6)	(150.6)
Income (1000s)	86.18	86.19	-0.010	75.59	84.42	92.85
	(37.86)	(37.60)	(0.269)	(33.52)	(36.48)	(39.52)
1(Rent)	0.022	0.023	0.000	0.019	0.023	0.024
	(0.14)	(0.14)	(0.001)	(0.11)	(0.14)	(0.15)
Single Family	0.96	1	-0.001	0.97	0.96	0.95
	(0.21)	(0)	(0.001)	(0.18)	(0.20)	(0.22)
Square Footage	1660	1658	1.68	1615	1637	1702
	(454)	(447)	(3.22)	(440)	(440)	(463)
F-Test p-Value			0.315			
1(Account Closed)	0.012	0.013		0.023	0.011	0.010
	0.11	0.11		0.15	0.10	0.10
Number of Households	39217	39275		14,055	33,016	30,913
Number of Bill Obs	726954	728623		261,721	614,809	576,387

*, **, ***: Different from zero with 90%, 95%, and 99% confidence, respectively.

"Number of Households" by normative categorization reflects the number of treatment or control households that were at any point in that category. The sum of these numbers across the three categories therefore is greater than the number of households in the experiment.

7.2 Treatment Effects

	I	II	III	IV	V
T x Post	-0.0175	-0.0192	-0.0191	-0.0208	-0.0189
	(0.0053)***	(0.0020)***	(0.0020)***	(0.0021)***	(0.0020)***
T x Quarterly x Post	0.0074	0.0085	0.0086	0.0080	0.0082
	(0.0082)	(0.0032)***	(0.0032)***	(0.0033)**	(0.0032)***
Post	-0.1167	-0.1135	-0.0465	-0.0873	-0.0062
	(0.0033)***	(0.0014)***	(0.0059)***	(0.0052)***	(0.0058)
Quarterly x Post	-0.0099	-0.0046	-0.0047	-0.0058	-0.0044
	(0.0058)*	(0.0022)**	(0.0022)**	(0.0023)**	(0.0022)**
Degree-Day Polynomial					Yes
Month x Year Dummies			Yes	Yes	Yes
House Fixed Effects		Yes	Yes		Yes
House x Month Fixed Effects				Yes	
Observations (thousands)	1,456	1,456	1,456	1,456	1,456
R^2	0.0057	0.0057	0.0472	0.0018	0.0499
F Statistic	5406	6412	7356	929	7188

*, **, ***: Different from zero with 90%, 95%, and 99% confidence, respectively.

Dependent variable is the household's average daily electricity consumption (kilowatt-hours), normalized by average control group consumption in the Post period.

7.3 Alternative Empirical Approaches

	Treatment Only	Treatment Only	In Logs
T x Post	-0.1327	-0.0206	-0.0134
	(0.0015)***	(0.0018)***	(0.0017)***
T x Quarterly x Post	0.0039	0.0038	0.0064
	(0.0023)*	(0.0023)	(0.0029)**
Post			-0.0413
			(0.0039)***
Quarterly x Post			-0.0062
			(0.0020)***
Degree-Day Polynomial		Yes	
Month Dummies		Yes	
Month x Year Dummies			Yes
House Fixed Effects	Yes	Yes	Yes
Observations (thousands)	727	727	1455
R^2	0.0189	0.0503	0.0579
F Statistic	6744	908	14043

*, **, ***: Different from zero with 90%, 95%, and 99% confidence, respectively.

Dependent variable for the first two specifications is the household's average daily electricity consumption (kilowatt-hours), normalized by average control group consumption in the Post period. For the third specification, it is the log of that value.

7.4 Decay of Quarterly Treatment Effects

	I	II
T x Quarterly x Post	0.0140 (0.0049)***	0.0140 (0.0049)***
T x Quarterly x Post (1st Bill)	-0.0081 (0.0048)*	
T x Quarterly x Post (2nd Bill)	-0.0067 (0.0044)	
T x Quarterly x Post (1st or Second Bill)		-0.0075 (0.0043)*
Quarterly x Post	-0.0214 (0.0034)***	-0.0213 (0.0034)***
Quarterly x Post (1st Bill)	0.0204 (0.0034)***	
Quarterly x Post (2nd Bill)	0.0244 (0.0031)***	
Quarterly x Post (1st or 2nd Bill)		0.0223 (0.0031)***
T x Bill Number Dummies	Yes	Yes
Bill Number Dummies	Yes	Yes
House Fixed Effects	Yes	Yes
Observations (thousands)	1,456	1,456
R^2	0.0449	0.0449
F Statistic	3705	3877

*, **, ***: Different from zero with 90%, 95%, and 99% confidence, respectively.

Dependent variable is the household's average daily electricity consumption (kilowatt-hours), normalized by average control group consumption in the Post period.

7.5 Heterogeneous Treatment Effects

	I	II	III
T x Post	-0.0186 (0.0018)***	-0.0189 (0.0018)***	-0.0189 (0.0018)***
T x Quarterly x Post	0.0082 (0.0028)***	0.0083 (0.0028)***	0.0084 (0.0028)***
Post	-0.0456 (0.0060)***	-0.0465 (0.0060)***	-0.0471 (0.0060)***
Quarterly x Post	-0.0055 (0.0020)***	-0.0055 (0.0020)***	-0.0056 (0.0020)***
T x Post x Baseline Usage	-0.0191 (0.0037)***	-0.0189 (0.0035)***	-0.0150 (0.0033)***
T x Post x Consumer Age	-0.0017 (0.0015)		
T x Post x Gas Heat	-0.0073 (0.0024)***	-0.0071 (0.0024)***	
T x Post x Household Size	0.0009 (0.0016)		
T x Post x House Age	0.0008 (0.0015)		
T x Post x log(House Value)	-0.0014 (0.0015)		
T x Post x log(Income)	-0.0010 (0.0018)		
T x Post x 1(Rent)	-0.0014 (0.0013)		
T x Post x Single Family	-0.0004 (0.0012)		
T x Post x Square Footage	0.0058 (0.0018)***	0.0045 (0.0016)***	
Month x Year Dummies	Yes	Yes	Yes
House Fixed Effects	Yes	Yes	Yes
Post x (X Variable) Controls	Yes	Yes	Yes
Observations (thousands)	1,456	1,456	1,456
R^2	0.0100	0.0100	0.0100
F Statistic	4828	7266	8414

*, **, ***: Different from zero with 90%, 95%, and 99% confidence, respectively.

Dependent variable is the household's average daily electricity consumption (kilowatt-hours), normalized by average control group consumption in the Post period.

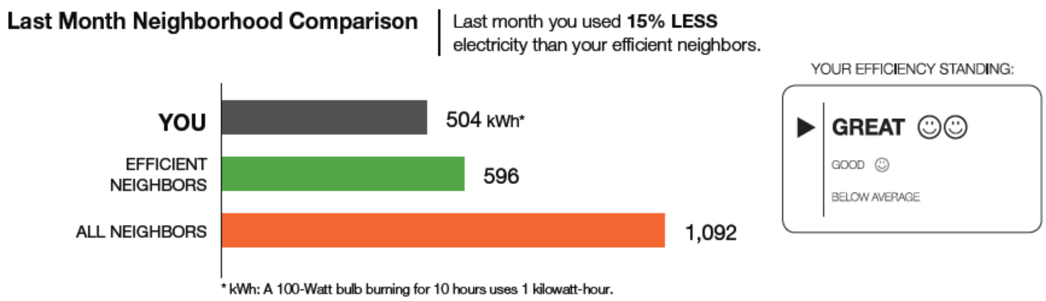
7.6 Profiling and Cost Effectiveness

Assignment Mechanism	*All*	*I*	*II*	*III*
ATE	-0.0191	-0.0343	-0.0346	-0.0347
	(0.0053)	(0.0035)	(0.0035)	(0.0036)
Electricity Bill Savings (dollars/household-year)	20.34	36.56	36.85	36.99
	(5.60)	(3.75)	(3.77)	(3.83)
Cost Effectiveness (cents/kwh saved)	5.31	2.95	2.93	2.92
	(1.46)	(0.30)	(0.30)	(0.30)
Percent Same as II	0.497	0.723		
Percent Same as III	0.498	0.677	0.684	

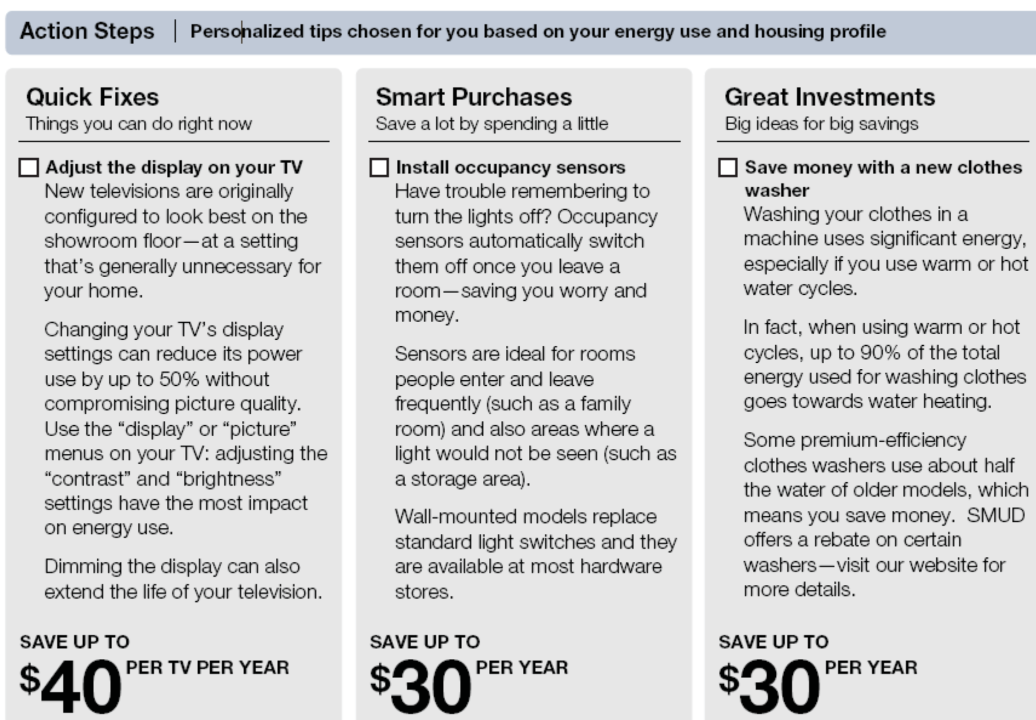
ATE is in percent of Control group usage in the post-treatment period.

8 Figures

8.1 Home Energy Reports: Social Comparison Module



8.2 Home Energy Reports: Action Steps Module



Action Steps | **Personalized tips chosen for you based on your energy use and housing profile**

Quick Fixes
Things you can do right now

☐ **Adjust the display on your TV**
New televisions are originally configured to look best on the showroom floor—at a setting that's generally unnecessary for your home.

Changing your TV's display settings can reduce its power use by up to 50% without compromising picture quality. Use the "display" or "picture" menus on your TV: adjusting the "contrast" and "brightness" settings have the most impact on energy use.

Dimming the display can also extend the life of your television.

SAVE UP TO
$40 **PER TV PER YEAR**

Smart Purchases
Save a lot by spending a little

☐ **Install occupancy sensors**
Have trouble remembering to turn the lights off? Occupancy sensors automatically switch them off once you leave a room—saving you worry and money.

Sensors are ideal for rooms people enter and leave frequently (such as a family room) and also areas where a light would not be seen (such as a storage area).

Wall-mounted models replace standard light switches and they are available at most hardware stores.

SAVE UP TO
$30 **PER YEAR**

Great Investments
Big ideas for big savings

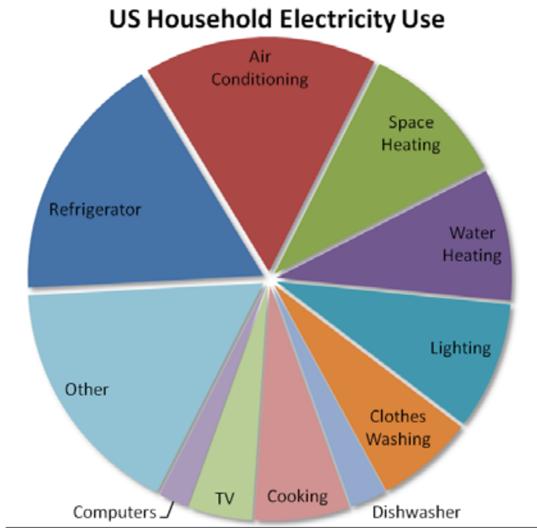
☐ **Save money with a new clothes washer**
Washing your clothes in a machine uses significant energy, especially if you use warm or hot water cycles.

In fact, when using warm or hot cycles, up to 90% of the total energy used for washing clothes goes towards water heating.

Some premium-efficiency clothes washers use about half the water of older models, which means you save money. SMUD offers a rebate on certain washers—visit our website for more details.

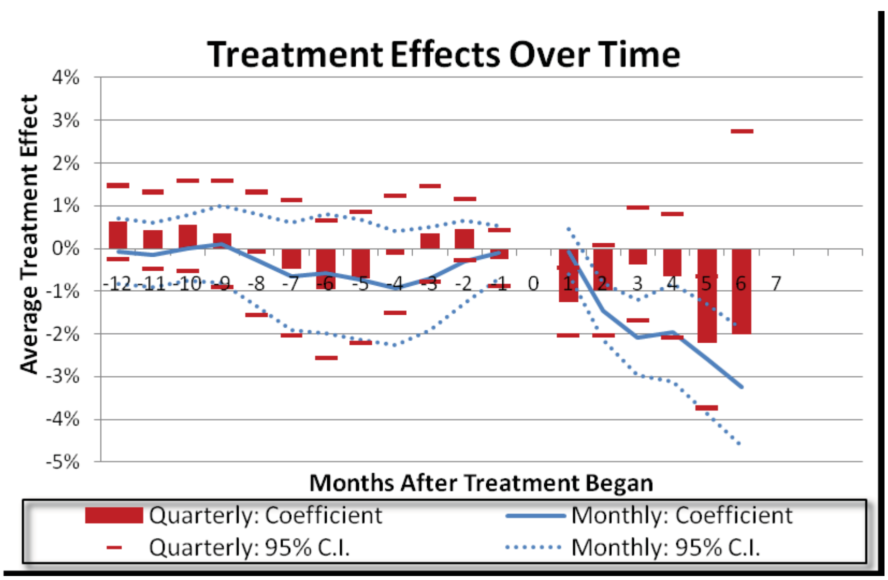
SAVE UP TO
$30 **PER YEAR**

8.3 US Household Electricity Use

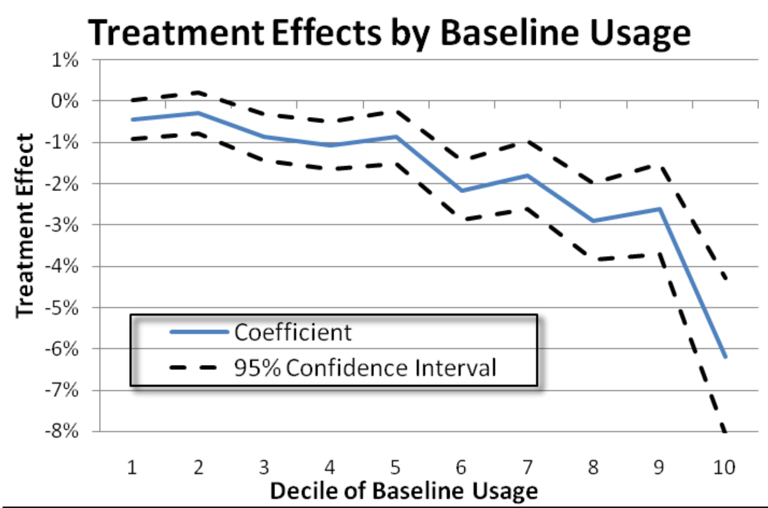


Source: US national average from 2001 Residential Energy Consumption Survey (US Energy Information Administration 2001).

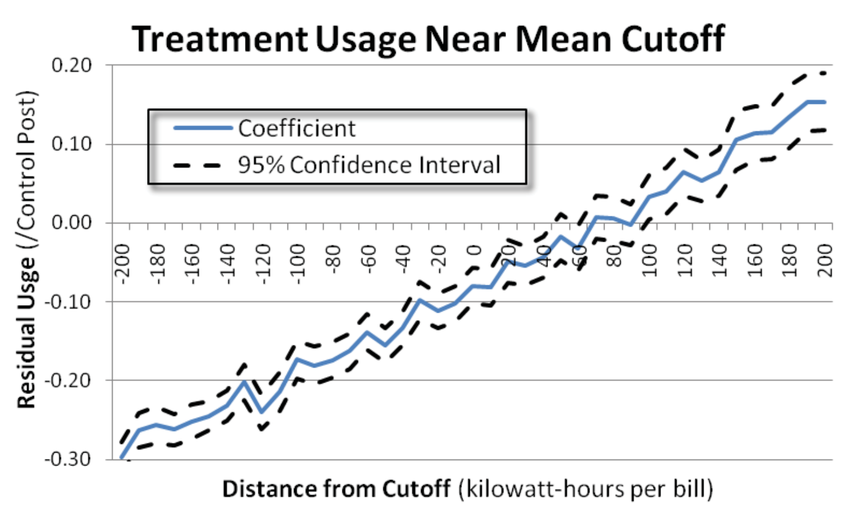
8.4 Treatment Effects Over Time



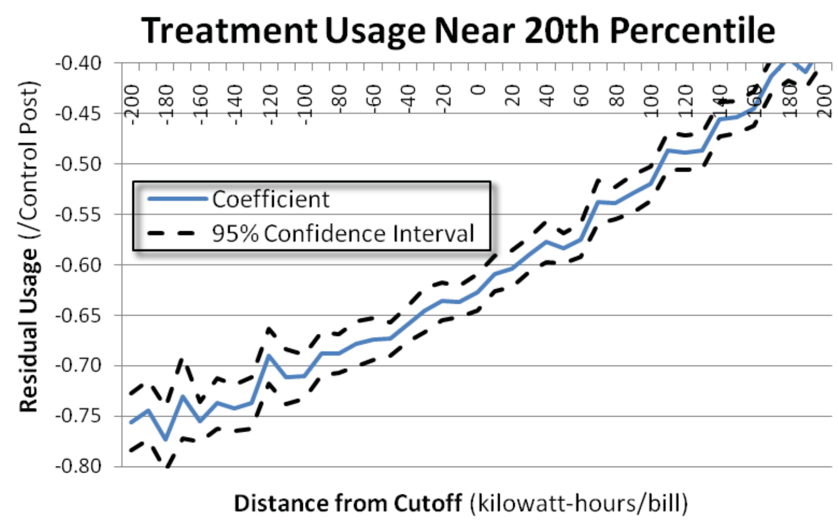
8.5 Treatment Effects by Decile of Baseline Usage



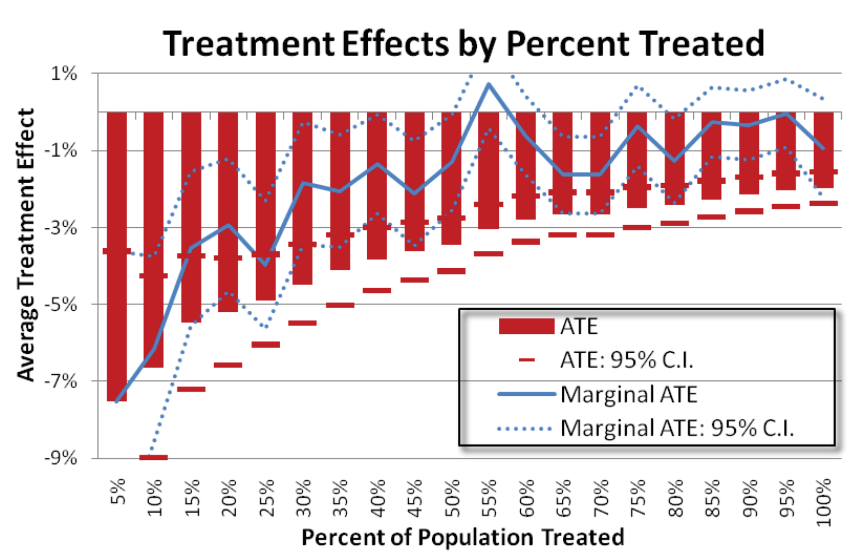
8.6 Treatment Group Near Mean Comparison Cutoff



8.7 Treatment Group Near 20th Percentile Cutoff



8.8 Gains from Profiling



Evaluation Report: OPOWER SMUD Pilot Year2

Presented to

OPOWER , Inc.

February 20, 2011

Presented by:

Kevin Cooney

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February 20, 2011

Re: OPOWER 2 ½ Year Results at Sacramento Municipal Utility District

To Whom it May Concern:

OPOWER is pleased to share the latest analysis of the nation's longest running behavioral energy program, our 35,000 household Home Energy Report deployment with Sacramento Municipal Utility District (SMUD). The analysis was led by Bill Provencher, Associate Director of the Navigant Consulting Energy Practice, and reviews data from April 2008 to October 2010.

Navigant confirms the persistence, and even increase, of savings over the program's lifetime.

The key findings of the updated report are:

- Year 2 savings = 2.89%, a 22% increase over Year 1
- Highest savings occur during the peak season: 3.56% savings in July and August of 2009
- **No sign of impact deterioration** over 30 months

This independent analysis validates OPOWER's internal assessment of the Home Energy Reports, and confirms the persistence and predictability of the Home Energy Reporting platform. This same M&V methodology is currently being employed to verify the impact of our program at 47 other utilities across the nation, where OPOWER is observing similar savings.

For more information about the SMUD analysis, or the impact of Home Energy Reports at other utilities, please contact results@opower.com.

Sincerely,

Ogi Kavazovic
VP, Strategy and Marketing

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Contents

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Executive Summary

Information technologies designed to assist and encourage customers to use less energy are increasing in the industry. OPOWER, Inc. offers an information program to help residential customers manage their electricity use by providing regular reports –called Home Electricity Reports—about the customer's electricity consumption. Along with other information, these reports compare a household's electricity use to that of its neighbors and suggest actions the household can take to reduce its electricity use. It is hypothesized that presentation of energy use in this comparative fashion creates a "social nudge" that induces households to reduce their electricity use.

This hypothesis is being tested in a three-year pilot of the OPOWER program in the Sacramento Municipal Utility District (SMUD) that began in spring 2008. The program consists of an experimental design across Census blocks in which blocks were randomly assigned to treatment and control groups. 35,000 single-family residential customers in the treatment group receive regular reports on how their energy use compares to their neighbors' energy use. Treatment households with high consumption in 2007 receive monthly reports, and households with low consumption receive quarterly reports. 50,000 single-family customers in the control group did not receive any reports. Billing data has been assembled for all customers beginning the year prior to the start of the program.

Several studies have examined the results of the first year of the SMUD OPOWER pilot program, including an analysis done by Summit Blue Consulting (now part of Navigant Consulting). All studies concluded that program savings in the first year was about 2.1%. The robustness of the savings estimates across studies is due largely to the experimental design of the program. The experimental design makes the identification of program savings robust to the specification of the econometric model used to estimate savings.

This report presents an evaluation of the first 29 months of the program, with an emphasis on the second year of the program. The main research questions addressed in the evaluation and presented in this report are the following:

A. Does the program continue to generate savings?
B. What is the trend in program savings? Is there a ramp-up period to savings? If so, for how long? Are savings now relatively stable, increasing, or falling?
C. Do program savings increase with usage?

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A. Does the program continue to generate savings?

The program continues to generate savings:

- Average savings in program Year 2 were 2.89% for high consumption (HC) households receiving monthly reports, and 1.70% for low consumption (LC) households receiving quarterly reports.
- Year 2 average household savings is 381 kWh for HC households and 104 kWh for LC households.
- Average household savings through the first 29 months of the program is 878 kWh for HC households and 234 kWh for LC households.

B. What is the trend in program savings?

Program savings are characterized by temperature-driven seasonal fluctuations around a baseline trend. For HC households, the baseline trend ramped up through the first 10-12 months and appears to have remained fairly constant since then:

- Average percent savings in program Year 2 are higher than in Year 1, 2.89% compared to 2.37%, which is a 22% increase in savings in the second year. The increase is statistically significant.
- Statistical analysis indicates that the long term trend for savings leveled off at about 10-12 months, and has remained fairly constant since then. In other words, after the first year of the program the fundamental effectiveness of the program does not appear to have changed substantially.
- Statistical analysis supports a long term savings trend of about 380 kWh per year, approximately 2.9% per year.
- Additional analysis after the program has been in place for a full three years, with data for at least three occurrences of each season, should give a better indication of whether the long term trend in savings is indeed constant or instead showing signs of rising or falling.

For LC households, program savings continue to trend upward:

- Average percent savings in program Year 2 are higher than in Year 1, 1.70% compared to 1.25%, which represents a 36% increase in savings.
- Statistical analysis indicates that program savings continue to trend upward through the first 29 months of the program.

C. Do program savings increase with electricity use?

For both HC and LC households, program savings reveal strong seasonal effects, with savings highest in the seasons of highest electricity use, summer and winter. For instance, in Year 2 (spring 2009-winter 2010) the average kWh savings for HC households in the seasonal sequence spring-summer-fall-winter was 80-123-84-97 kWh. The same sequence for LC households was 13-36-20-33 kWh.

The seasonality of savings is especially apparent in the pronounced rise in savings in the months of July and August. For HC households the percent savings for these months is 3.56% in summer 2009 and 3.27% in summer 2010. The difference between these percent savings is not statistically significant at any reasonable level of significance (the t-statistic on the difference is 1.2).

D. Graphical summary

Figures E1 and E2 present the trends in annual program savings for HC and LC households over months 6-29 of the OPOWER program. The figures abstract from seasonal fluctuations in program savings by setting heating and cooling degree days at their annual averages. The figures illustrate several of the points made above:

- For HC households, program savings appear to have remained constant on an annual basis after an initial ramp-up period of about 10-12 months; the tail end of the ramp-up period is apparent in months 6-12 of figure E1. The long run annual savings of about 380 kWh is a savings of approximately 2.9% per year.
- For LC households, program savings continue to trend upward.

Figure E3 presents monthly fluctuations in program savings directly attributable to fluctuations in temperatures during the program period. The figure illustrates that:
- Program savings are highest in the summer and winter months, with the summer response especially pronounced for HC households;
- Fluctuations follow the same pattern for HC and LC households, with fluctuations for HC household scaled up by a factor of about 2.5 relative to LC households.

Figure E1. Trend in annual program savings, HC households, program months 6-29 (September 2009-August 2010).

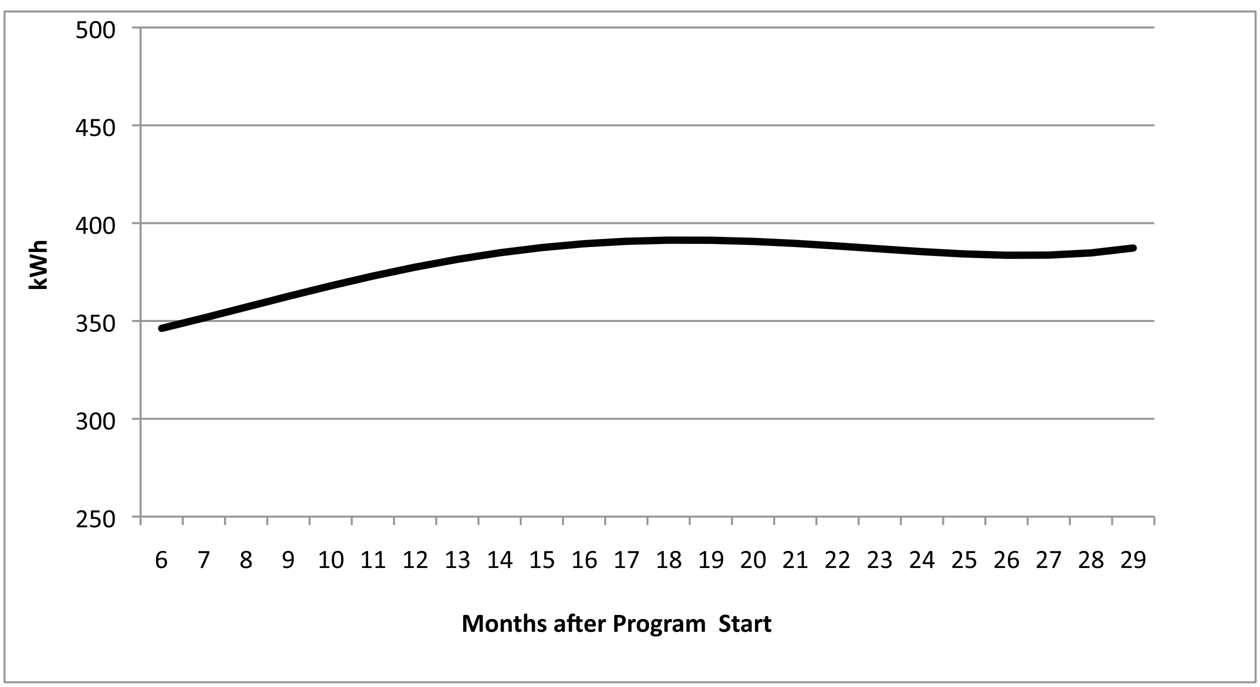

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Figure E2. Trend in annual program savings, LC households, program months 6-29 (September 2009-August 2010).

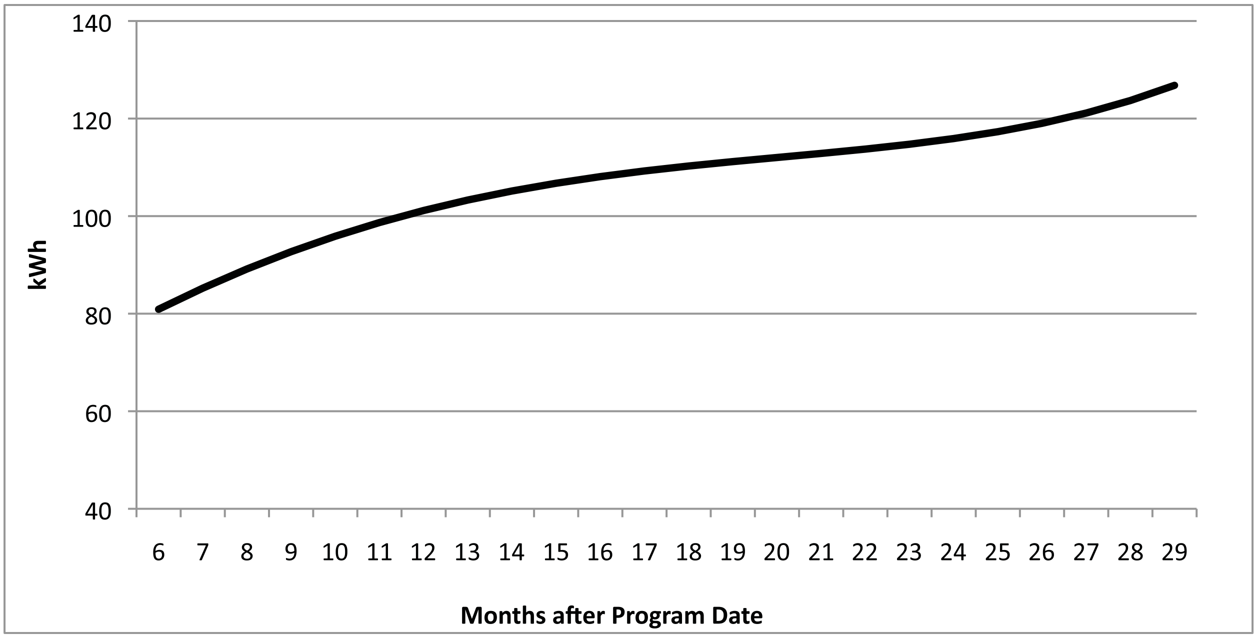
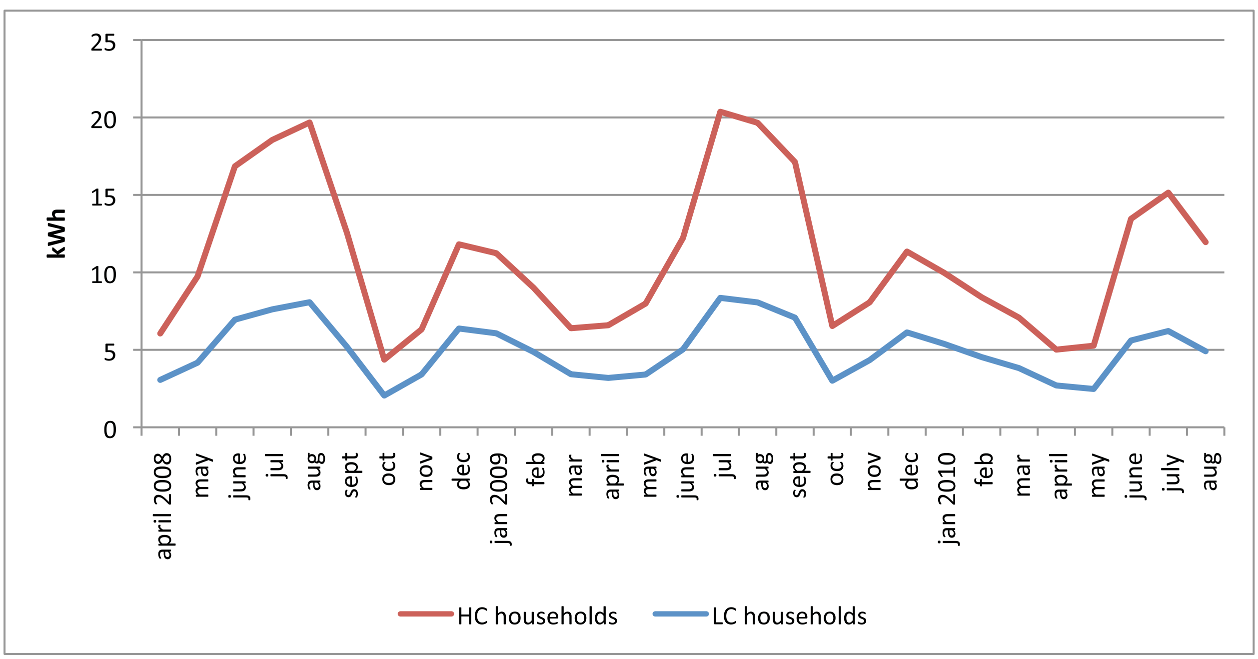


Figure E3. Estimate of temperature-related monthly program savings



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I. Program Description and Evaluation Objectives

OPOWER, Inc. offers an information program to help residential customers manage their electricity use by providing regular reports –called Home Electricity Reports—about the customer's electricity consumption. Along with other information, these reports compare a household's electricity use to that of its neighbors and suggest actions the household can take to reduce its electricity use. It is hypothesized that presentation of energy use in this comparative fashion creates a "social nudge" that induces households to reduce their electricity use.

This hypothesis is being tested in a three-year pilot of the OPOWER program in the Sacramento Municipal Utility District (SMUD) that began in spring 2008, with initial reports mailed between March 14 and April 30. The objective of the pilot is to test whether, and to what extent, the OPOWER program reduces residential electricity consumption. The reports give customers three types of information: a) how their recent electricity use compares to their energy use in the past; b) tips on how to reduce electricity consumption, some of which are tailored to the customer's circumstances (e.g. customers with electric heat receive information on how to reduce electricity consumption by electric heating systems); and c) most strikingly, information on how their electricity use compares to that of neighbors with similar homes.

Importantly, the program was set up as an experimental design. Households were randomly assigned between those that receive the Home Electricity Reports (treatment group) and those that do not receive them (control group), by census block. In particular, sets of 5 contiguous census blocks were randomly assigned in turn to the treatment and then the control group until the threshold 35,000 households in the treatment group was reached, at which point the remaining census blocks were assigned to the control group, generating about 50,000 control households. Ayres et al. established that treatment households generally are not different than control households, either statistically or substantively, on a number of characteristics, including house value, heat type (gas vs. electric), square footage (statistically significant, but with an average of 1,737 sq. ft. for treatment households and 1,753 sq. ft. for control households), and quartile income group.[1]

Most treatment households (24,761) received reports on a monthly basis, and the remainder (9,903) received the reports on a quarterly basis. Assignment to monthly vs. quarterly reports was not random; households receiving monthly reports were generally higher energy consumers than households receiving quarterly reports. For instance, among the treatment households examined in the analysis presented in this report, 98.8% of those receiving monthly reports consumed more than 20 kWh per day in 2008, whereas only 16.6% of those receiving quarterly reports consumed more than 20 kWh per day.

Several studies have examined the results of the first year of the OPOWER program, including an analysis done by Summit Blue Consulting (now part of Navigant Consulting).[2] All studies

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[1] Ayres, Raseman and Shih, 2009, Table A1, pg. 29. See footnote 2 for full citation.
[2] These studies include:

Ayres, I., S. Raseman and A. Shih. "Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage", NBER working paper no. 15386, September 2009.

Costa, D.L. and M.E. Kahn. "Energy Conservation "Nudges" and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment", NBER working paper no. 15939, April 2010.

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concluded that program savings in the first year was about 2.1%. The robustness of the savings estimates across studies is due largely to the experimental design of the program. The experimental design makes the identification of program savings robust to the specification of the econometric model used to estimate program savings.

This report presents an evaluation of the first 29 months of the program, with an emphasis on the second year of the program. The main research questions addressed in the evaluation, and presented in this report, are the following:

D. Does the program continue to generate savings?
E. What is the trend in program savings? Is there a ramp-up period to savings? If so, how long? Are savings now relatively stable, increasing, or falling?
F. Do program savings increase with usage?

Summit Blue Consulting (now a part of Navigant Consulting). "Impact Evaluation of OPOWER SMUD Pilot Study". September 2009, unpublished.

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II. Impact Evaluation Methods

Two statistical analyses were used to estimate savings during the first year of the program. These methods are a) difference-in-difference (DID) analysis, and b) linear fixed effects regression(LFER) analysis. Below we describe these methods, emphasizing that the DID estimate of program savings can be recovered using a simple LFER analysis.

A. Difference-in-Difference (DID) analysis

Assuming random assignment of treatment and control customers, a simple difference-in-difference (DID) statistic provides an unbiased estimate of the average customer savings in energy use (measured in kWh) from the treatment for a given period, such as a year or a season. The basic logic of the estimator is that the average difference among treatment customers in energy consumption before treatment and after treatment is due in part to the treatment and in part to unobserved temporal factors affecting energy consumption. A set of control customers is used to isolate the part that is due to unobserved temporal factors. Calculating this same difference for the set of control customers and subtracting this value from that obtained for treatment customers isolates the portion of the change in consumption among treatment customers that is due to the treatment (i.e., the OPOWER program).

Formally, we denote by $\overline{kWh}_{pg}$ the average daily kWh use in period *p* (*p*=0 for the pre-treatment period, *p*=1 for the post-treatment period) by customers in group *g* (*g*=0 for the control group, *g*=1 for the treatment group).[3] The length of time over which average daily kWh is measured depends on the question being asked; for instance, the period could be a year or a season. The DID statistic is the difference between the control and treatment groups in the *change* in their annual rate of kWh use across the pre- and post-treatment periods. Formally,

$$\begin{aligned} Treatment\ Effect &= DID = \left(\overline{kWh}_{11} - \overline{kWh}_{01}\right) - \left(\overline{kWh}_{10} - \overline{kWh}_{00}\right) \\ &= Dif\left(\overline{kWh}_{1}\right) - Dif\left(\overline{kWh}_{0}\right) \end{aligned}, \tag{1}$$

where $Dif\left(\overline{kWh}_{g}\right)$ is the *difference* in average daily kWh consumption across periods for customers in group g. Dividing the DID statistic by the average daily kWh consumption of the treatment group in the post-treatment period gives the proportional reduction from treatment,

$$Proportional\ Treatment\ Effect = \frac{Dif\left(\overline{kWh}\right)}{\overline{kWh}_{11}}. \tag{2}$$

B. Linear Fixed Effects Regression (LFER) model

The simplest version of a linear fixed effects regression (LFER) model convenient for exposition is one in which average daily consumption of kWh by customer *k* in bill t, denoted by ADU_{kt}, is a function of three terms: the binary variable $Treatment_k$, taking a value of 0 if customer *k* is

[3] Both the control and treatment groups could be subsets, such as the set of high consumption households.

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assigned to the control group, and 1 if assigned to the treatment group; the binary variable $Post_t$, taking a value of 0 if bill t is before the customer's *program start date* and 1 if the bill is received on or after the program start date; and the interaction between these variables, $Treatment_k \cdot Post_t$. Formally,

$$ADU_{kt} = \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Treatment_k \cdot Post_t + \varepsilon_{kt} \tag{3}$$

We refer to this model as the "Basic LFER model". Three observations a**b**out this specification deserve comment. First, the coefficient α_{0k} captures *all* customer-specific effects on electricity use that do not change over time, including those that are unobservable. Second, α_1 captures the average effect *among control customers* of being in the post-treatment period. In other words, it captures the effects of exogenous factors, such as an economic recession, that affect all customers in the post-treatment period but not in the pre-treatment period. Third, $\alpha_1 + \alpha_2$ captures the average effect *among treatment customers* of being in the post-treatment period, and so the effect directly attributable to the OPOWER program is captured by the coefficient α_2. In other words, this coefficient captures the *difference-in-difference* in average daily kWh use between the treatment group and the control group across the pre- and post-treatment periods. Consequently the DID statistic can be estimated by simply estimating equation (3).

Expanding the basic LFER model to account for degree days

In a second model the simple LFER model described above is expanded to include two weather-related variables: heating degree days per day ($HDDd_t$) in bill period t, and cooling degree days per day, $CDDd_t$, For each of these, four terms are added to the model: the variable itself; the variable interacted with $Treatment_k$ to capture differential effects of the variable specific to the treatment group; the variable interacted with $Post_t$ to capture differential effects of the variable due to exogenous shocks across the pre- and post-treatment periods; and the variable interacted with the interaction $Treatment_k \cdot Post_t$ to capture the effect of the variable on the treatment response (that is, how the variable affects program savings).

Formally, we expand our basic LFER model to the following:

$$\begin{aligned} ADU_{kt} &= \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Treatment_k \cdot Post_t \\ &+ \beta_0 HDDd_t + \beta_1 HDDd_t \cdot Treatment_k + \beta_2 HDDd_t \cdot Post_t + \beta_3 HDDd_t \cdot Treatment_k \cdot Post_t \\ &+ \gamma_0 CDDd_t + \gamma_1 CDDd_t \cdot Treatment_k + \gamma_2 CDDd_t \cdot Post_t + \gamma_3 CDDd_t \cdot Treatment_k \cdot Post_t + \varepsilon_{kt} \end{aligned} \tag{4}$$

We refer to this model as the "degree day model". In this model, the average daily treatment effect (ADTE) is the sum of the terms involving the variable $Treatment_k$:

$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3 CDDd_t \, . \tag{5}$$

Note, then, that the treatment effect changes across seasons because of seasonal changes in $HDDd$ and $CDDd$. The coefficients on these variables in (5) indicate the average effect on a customer's program savings of a 1-unit increase in heating or cooling degree days.

Expanding the degree day model to examine savings trends

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The second objective of the evaluation (see page 7) is to determine the length of a ramp-up period and whether the trend in program savings is increasing, decreasing, or remaining steady. We address this objective by including in the LFER model trend variables involving the root variable $PostTrend_t$, which takes a value of 0 in the period before the customer's program start date and increases by 1 with each bill received by the customer beginning with the program start date. Consider, for instance, the following linear trend:

$$\begin{aligned} ADU_{kt} = {} & \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Treatment_k \cdot Post_t \\ & + \beta_0 HDDd_t + \beta_1 HDDd_t \cdot Treatment_k + \beta_2 HDDd_t \cdot Post_t + \beta_3 HDDd_t \cdot Treatment_k \cdot Post_t \\ & + \gamma_0 CDDd_t + \gamma_1 CDDd_t \cdot Treatment_k + \gamma_2 CDDd_t \cdot Post_t + \gamma_3 CDDd_t \cdot Treatment_k \cdot Post_t \\ & + \lambda_0 PostTrend_t + \lambda_1 Treatment_k \cdot PostTrend_t + \varepsilon_k \end{aligned} \tag{6}$$

Note that in this specification the root variable $PostTrend_t$ appears both separately and interacted with the treatment variable $Treatment_k$. This specification recognizes that energy consumption in the post-treatment period may be trending quite apart from the program effect, and uses the interaction with the treatment variable to identify whether the program is causing a divergence from this general trend.

The problem with a linear trend is that it is not sufficiently flexible to allow for a period of stasis in the treatment effect, whereby, after correcting for heating and cooling degree days, the program settles down into a fairly constant rate of program savings. With a linear trend the program effect is constrained to be always increasing, always decreasing, or always constant. This is not a sensible model for analyzing long term trends given that the program quite likely involves an initial ramp-up period.

A quadratic specification would provide greater flexibility –it allows savings to rise and then fall—but it too is not flexible enough to account for periods of stasis. With this in mind, we estimate LFER models with polynomial trends ranging from 1st order (linear) to 4th order (quartic). Increasing the polynomial trend increases the size of the LFER model by two terms involving the root variable $PostTrend_t$. For instance, the LFER model with a quadratic trend takes the form,

$$\begin{aligned} ADU_{kt} = {} & \alpha_{0k} + \alpha_1 Post_t + \alpha_2 Treatment_k \cdot Post_t \\ & + \beta_0 HDDd_t + \beta_1 HDDd_t \cdot Treatment_k + \beta_2 HDDd_t \cdot Post_t + \beta_3 HDDd_t \cdot Treatment_k \cdot Post_t \\ & + \gamma_0 CDDd_t + \gamma_1 CDDd_t \cdot Treatment_k + \gamma_2 CDDd_t \cdot Post_t + \gamma_3 CDDd_t \cdot Treatment_k \cdot Post_t \\ & + \lambda_0 PostTrend_t + \lambda_2 Treatment_k \cdot PostTrend_t + \lambda_3 PostTrend_t^2 + \lambda_4 Treatment_k \cdot PostTrend_t^2 + \varepsilon_k \end{aligned} \tag{7}$$

The treatment effect for the linear trend model in (6) is the following:

$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3 CDDd_t + \lambda_1 \cdot PostTrend_t. \tag{8}$$

Note that the treatment effect depends on the time elapsed since the beginning of the program. Similarly, the treatment effect for the quadratic trend is,

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$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3 CDDd_t + \lambda_2 \cdot PostTrend_t + \lambda_4 PostTrend_t^2 . \quad (9)$$

Following this pattern, the treatment effects for the cubic and quartic trend models are:

$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3 CDDd_t + \lambda_2 \cdot PostTrend_t + \lambda_4 PostTrend_t^2 + \lambda_6 PostTrend_t^3$$
$$ADTE_{kt} = \alpha_2 + \beta_3 HDDd_t + \gamma_3 CDDd_t + \lambda_2 \cdot PostTrend_t + \lambda_4 PostTrend_t^2 + \lambda_6 PostTrend_t^3 + \lambda_8 PostTrend_t^4$$

(10)

Increasing the size of the polynomial provides great flexibility in fitting the model to the program effect, though at the cost of increasing the number of "turning points" in the fit. For this reason the observation of a turning point, especially at the edge of the data range, should be interpreted with considerable caution. A turning point could be an artifact of the parametric form of the model used to fit the data, rather than an actual change in the trend in program savings. We limited the analysis to polynomial trends of 4th order and lower because for polynomial fits up to the fourth order, all terms of the polynomial involving the interaction with $Treatment_k$ were statistically significant. Higher-order polynomials generated nonsignificant terms.

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III. Impact Evaluation Results

A. Results of DID estimation

Results for the DID estimation are presented in Table 3.1. Results are graphically summarized in Figure 3.1-3.4. Relevant baseline consumption and heating and cooling degree days for the various periods of the analysis are presented in Table A.1 in Appendix A.

For the analysis of annual savings the sample of treatment and control customers was restricted to those with:

- 12 bills in the 375 days before the customer's program start date;
- 12 bills in the 355 days after the customer's program start date, the program start date inclusive (first year of the program); and
- 12 bills in the subsequent 375 days (second year of the program).

A customer's program start date was the date of the first bill *after* the bill in which the first report was included. The appropriate point of reference for evaluating the program is the program start date, rather than the bill date of first receipt of the report, because it is the former date that includes the initial response of the customer to the report information. The departure from exactly 365 days before and after the program start date in the specification of the pre- and post-treatment periods is to account for small deviations in the actual delivery dates for bills.

The analysis of seasonal effects restricted the data to bills falling within season dates.[4] To be included in a seasonal analysis a customer must have received 2-4 bills in both the pre-treatment and post-treatment seasons. The pre-treatment periods for seasonal analyses were summer 2007, fall 2007, winter 2007-08, and spring 2008.

The following results emerge from Table 3.1 and Figures 3.1-3.4:

- *Over the 30-month period, savings averaged about 2.6% for high consumption (HC) households and about 1.5% for low consumption (LC) households;*

- *For both HC and LC households, second year savings were greater than first year savings. For HC households, savings were 2.32% in the first year and 2.85% in the second year, and for LC households savings were 1.30% in the first year and 1.79% in the second year.*[5]
- *Over the past year the percent savings for HC households has remained constant at about 2.7% per year;*

- *The percent savings for LC households appears still to be trending upwards after 30 months.*

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[4] Season dates were Fall: September 15-December 14; Winter: December 15-March 14; Spring: March 15-June 14; Summer: June 15-September 14.
[5] Recent studies of the first year of the SMUD OPOWER program, including the one conducted by Summit Blue/Navigant, report savings of roughly 2.1%. This figure applies to HC and LC households combined. In our analysis, combining HC and LC households generates first year savings of 2.1%. The heavy weighting towards the HC estimate reflects the greater number of HC households and their high consumption levels.

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Extension of DID results: Examination of the summer months July-August

As requested we conducted a DID analysis of the two summer months July and August. Before presenting these results we use the illustration in Figure 3.5 to emphasize several important caveats about examining treatment effects using billing data over very short time horizons (one or two months). The figure considers a one-month billing period (July) and assumes that the billing of these households is uniformly distributed over the month –a good approximation of the billing data in this evaluation. The dates of June 1 and July 31 are covered by only one out of every 31 July bills (about 3.2%); the dates of June 2 and July 30 covered by two out of every 31 July bills (about 6.4%); June 3 and July 29 are covered by three out of every 31 July bills; and so on, with July 1 covered by *all* bills. This pyramidal sampling has several implications:

1. An analysis of bills at the monthly level is not an analysis of the treatment effect for the month per se, but rather is an analysis of the treatment effect *centered on the first day of the month*.
2. The estimate of the treatment effect is much more heavily influenced by unobserved events around the 1st of the month than by unobserved events late in the month or early in the previous month, suggesting correlated errors across households according to bill dates;
3. Analysis of the treatment effect on a monthly basis will exhibit greater volatility than truly applies on a monthly basis (where each day of the month receives an equal number of observations), because of the "center-weighting " illustrated in Figure 3.5.

The first point above—that analyzing data by the bill month does not give the treatment effect for the month, but rather a weighted estimate for the effect centered on the first of the month—is especially salient in the case of July because July 4th weekends can be 3 or 4 days long, and thus behavior during this period has an inordinate effect –inordinate if the analyst falsely believes that the measurement applies to average July behavior—on the estimate of the treatment effect.

Extending the analysis period serves to eliminate or at least substantially reduce the sampling issues raised above. Figure 3.6 considers the probability that a date is represented in a household's bills dated between July 15 and September 15, the bill dates that best cover the period July-August. Every household has a bill covering July 15-August 15. The 30-day plateau implies lower correlation of errors across households and reduced volatility. The plateau is centered on August 1.

Figures 3.7-3.8 present DID estimation results for July-August 2008, 2009, and 2010 for high consumption (HC) and low consumption (LC) households, respectively. Relevant baseline consumption and heating and cooling degree days are presented in Table A.1 in Appendix A. In the analysis we used bill dates between July 15 and September 15. If instead we had used bills in the period July 1- August 31 –the intuitive selection criterion for a July-August analysis—the analysis would have involved a 30-day plateau extending from *July 1 –July 30* and centered on July 15. Results are presented in terms of the percent of the average household kWh consumption for the time period, with actual kWh savings indicated in the figures. For HC households the percent savings rises from 2.97% in summer 2008 to 3.56% in summer 2009, before falling to 3.27% in summer 2010. The difference between percent savings in the summers of 2009 and 2010 is not statistically significant at any reasonable level of significance (t-statistic on the difference =1.2).

For LC households the percent savings rises from 1.31% in summer 2008 to 2.28% in summer 2009 to 2.66% in summer 2010. As with HC households, the difference between percent savings in the summers of 2009 and 2010 is not statistically significant (t-statistic on the difference =0.85).

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Table 3.1. DID Seasonal Estimates of Program Savings[a]

Period	Statistic	Estimate for HC Households (standard error)	Estimate for LC Households (standard error)
First Year (April 2008- March 2009)	Average percent savings	2.37% (0.11%)	1.25% (0.18%)
	Average savings per customer (kWh)	317 (15)	76 (25)
Second Year (April 2009- March 2010)	Average percent savings	2.89% (0.11%)	1.70% (0.18%)
	Average savings per customer (kWh)	381 (14)	104 (11)
Summer 2008 (June 15-Sept 14)	Average percent savings	2.63% (0.12%)	0.94% 0.21%)
	Average savings per customer (kWh)	105 (5)	18 (4)
Fall 2008 (Sept 15-Dec 14)	Average percent savings	2.30% (0.14%)	1.31% (0.27%)
	Average savings per customer (kWh)	69 (4)	18 (4)
Winter 2008-09 (Dec 15 - March 15)	Average percent savings	2.65% (0.12%)	1.82% (0.23%)
	Average savings per customer (kWh)	95 (4)	28 (4)
Spring 2009 (March 15 -June 14)	Average percent savings	2.81% (0.15%)	1.02% (0.22%)
	Average savings per customer (kWh)	80 (4)	13 (3)
Summer 2009 (June 15 -Sept 14)	Average percent savings	3.27% (0.13%)	2.00% (0.24%)
	Average savings per customer (kWh)	123 (5)	36 (4)
Fall 2009 (Sept 15-Dec 14)	Average percent savings	2.70% (0.14%)	1.42% (0.29%)
	Average savings per customer (kWh)	84 (4)	20 (4)

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Period	Statistic	Estimate for HC Households (standard error)	Estimate for LC Households (standard error)
Winter 2009-10 (Dec 15 - March 14)	Average percent savings	2.81% (0.12%)	2.11% (0.26%)
	Average savings per customer (kWh)	97 (4)	33 (4)
Spring 2010 (March 15 -June 14)	Average percent savings	2.73% (0.15%)	1.16% (0.23%)
	Average savings per customer (kWh)	75 (4)	15 (3)
Summer 2010 (June 15 -Sept 14)	Average percent savings	2.99% (0.18%)	2.29% (0.33%)
Sample Treatment= 18,554 *Sample Control= 27,346*	Average savings per customer (kWh)	105 (6)	39 (5)

[a]Except for minor variations, sample size for all seasons except summer 2010 is 20,200 for high consumption (monthly reports) treatment households, 29,800 for high consumption control households, 8,300 for low consumption (quarterly reports) treatment households, and 12,200 for low consumption control households. In summer 2010, SMUD reduced the number of treatment households by 10,000, and so in the analysis of summer 2010 the samples are 13,148 HC treatment households and 19,385 HC control households, 5,406 LC treatment households, and 7,961 LC control households. The reduction was done to examine the persistence of effects after discontinuation of the Home Electricity Reports, and was done by random assignment.

Figure 3.1. DID Estimates of Average Household Seasonal Savings (kWh) with 95% Confidence Intervals; *HC households (monthly reports)*

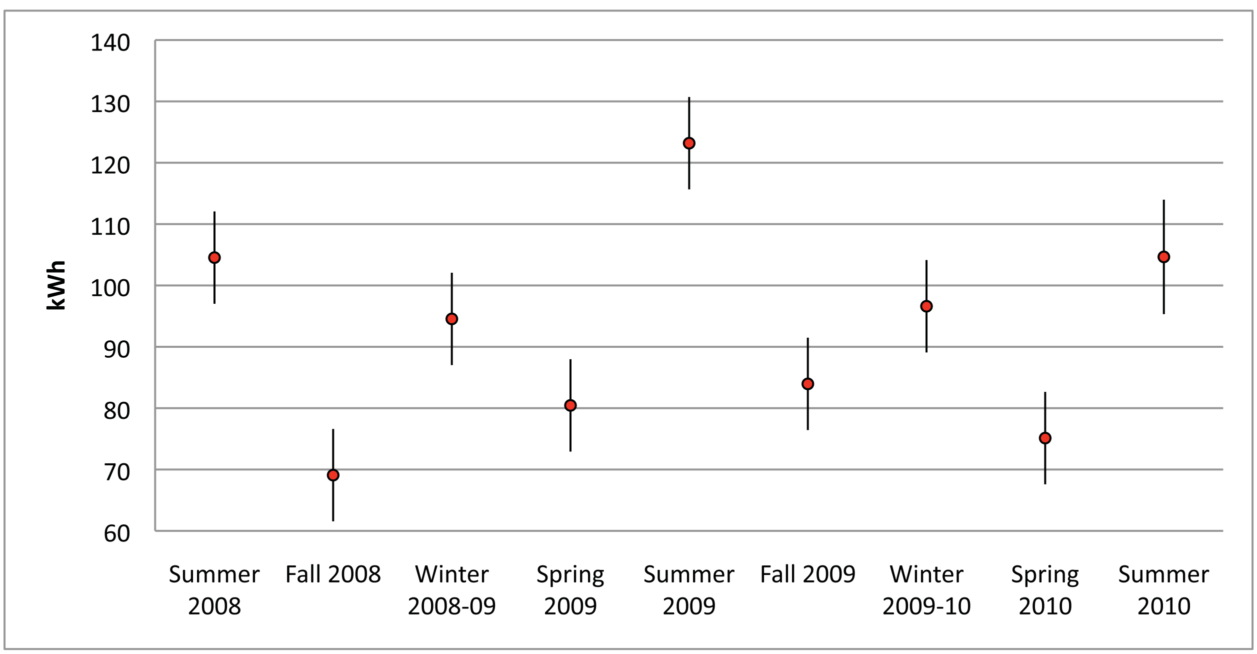

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Figure 3.2. DID Estimates of Percent Seasonal Savings with 95% Confidence Intervals; *HC households (monthly reports)*

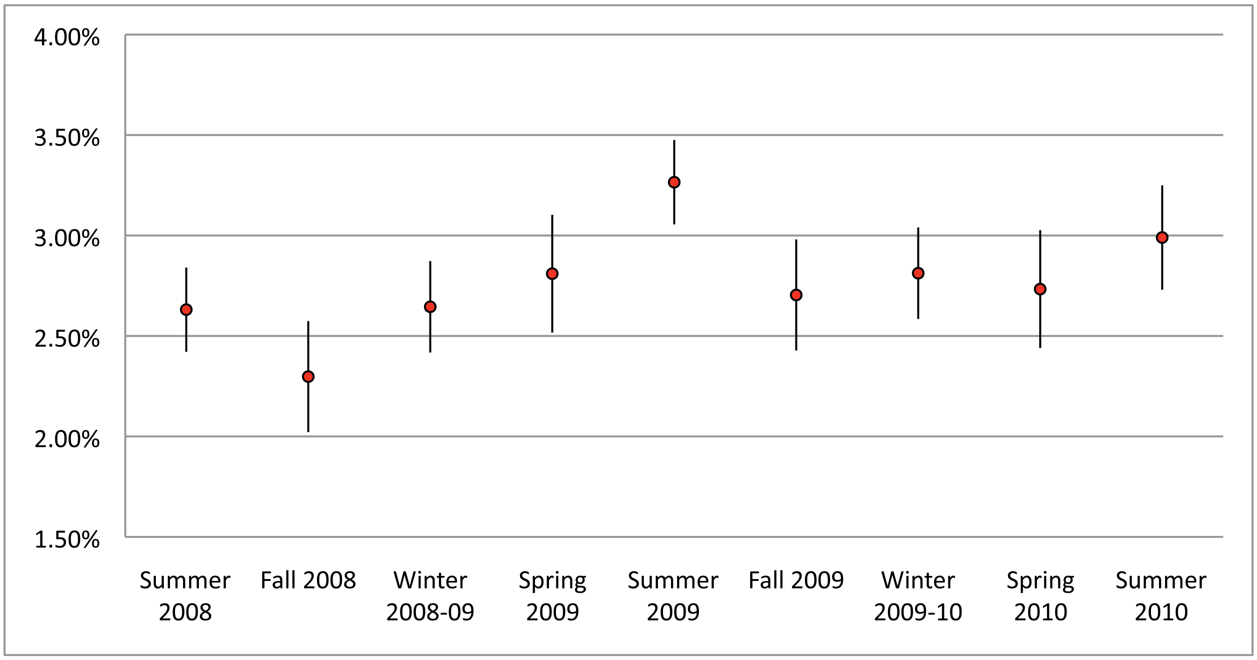

Figure 3.3. DID Estimates of Average Household Seasonal Savings with 95% Confidence Intervals; *LC households (quarterly reports)*

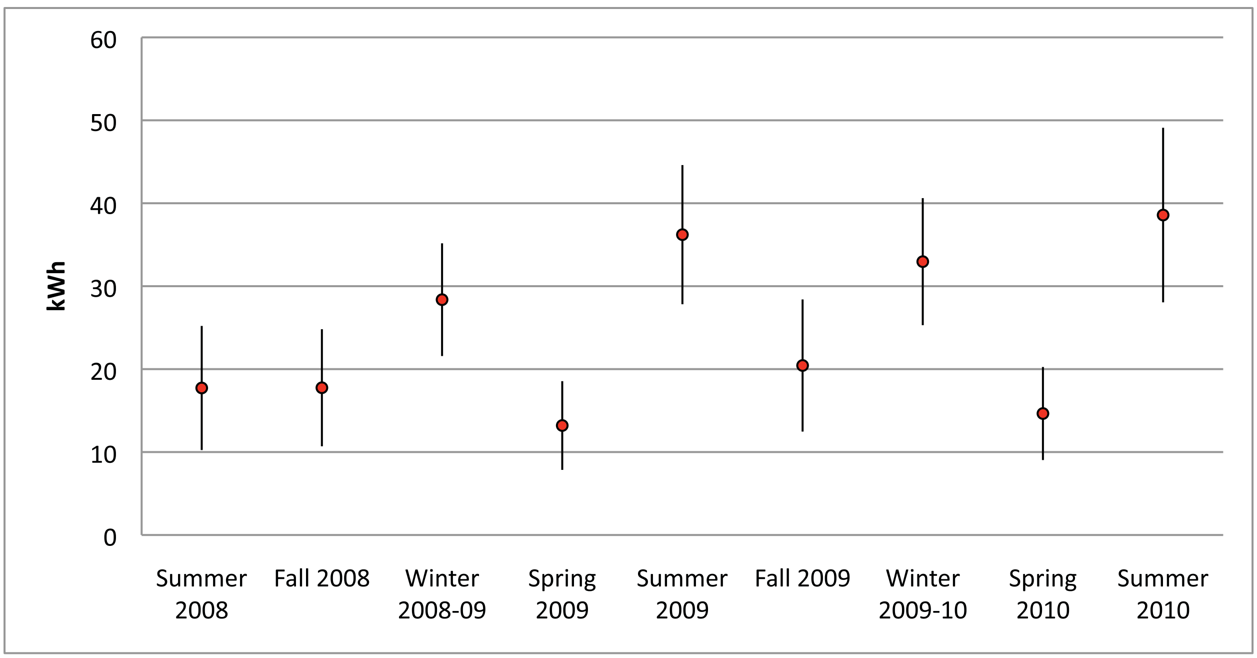

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Figure 3.4. DID Estimates of Seasonal Percent Savings with 95% Confidence Intervals; *LC households (quarterly reports)*

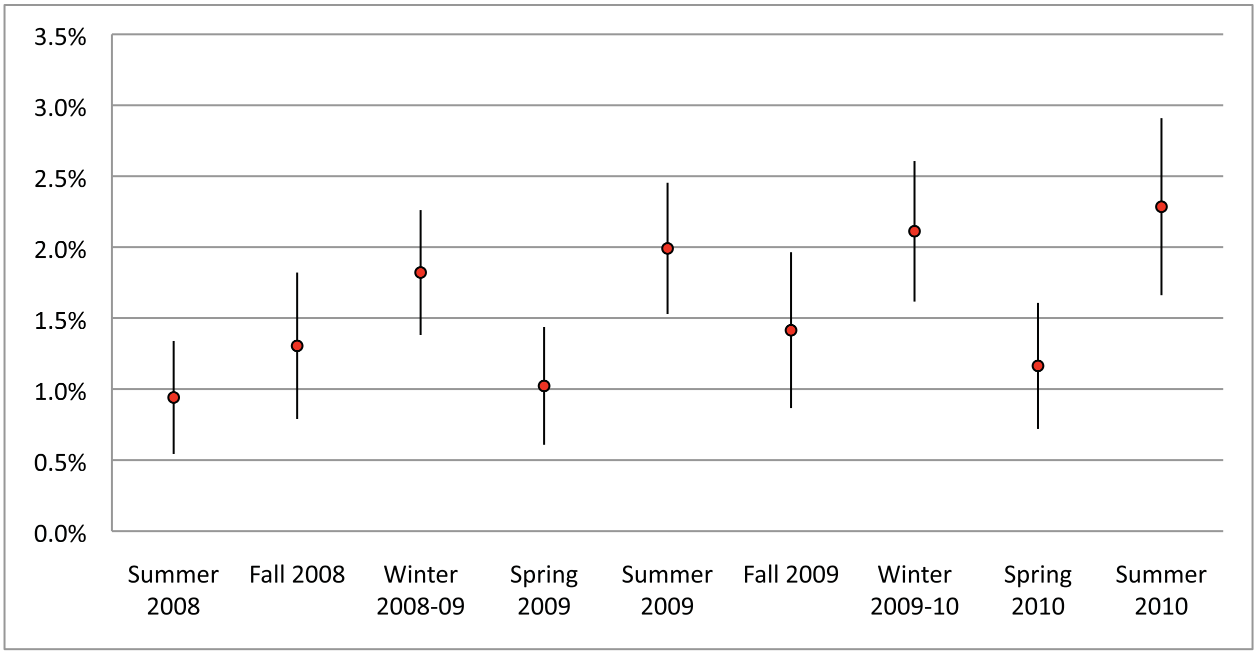

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Figure 3.5. Probability that a Date is Represented in a July Bill

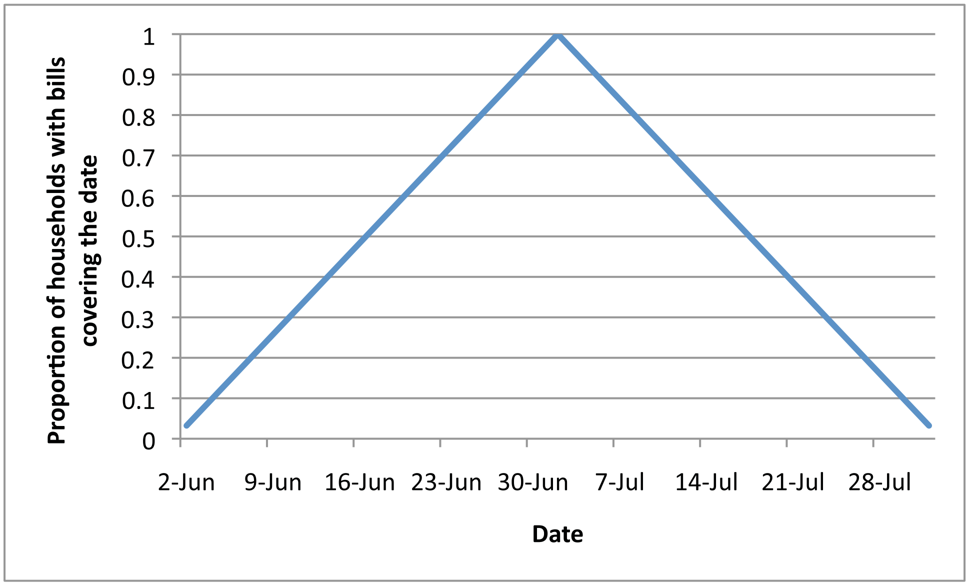

Figure 3.6. Probability that a Date is Represented in a Household's Bills Dated between July 15 and September 15

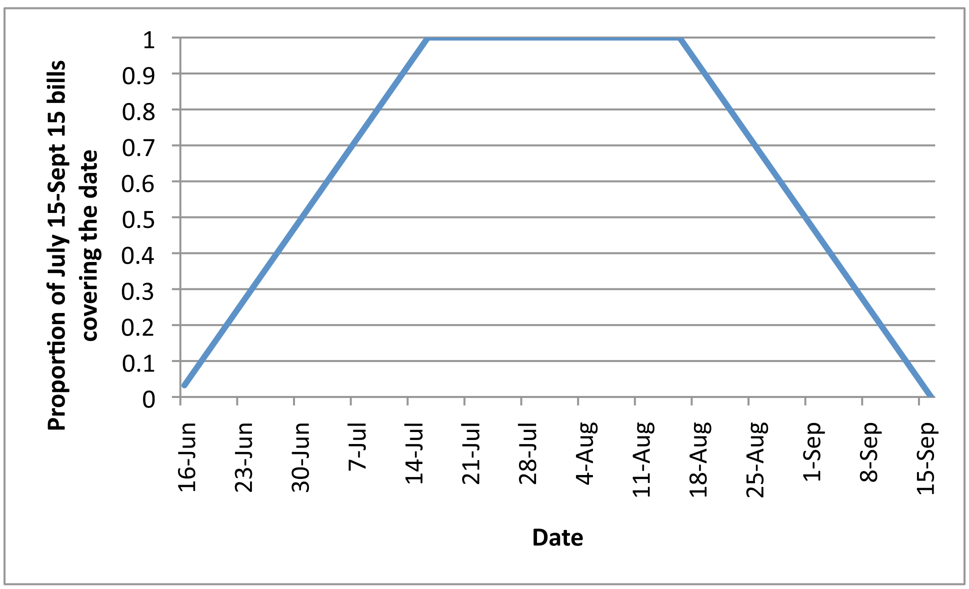

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Figure 3.7. DID Estimates of July-August Average Household Percent Savings with 95% Confidence Intervals, with kWh savings indicated, *HC households (monthly reports)*

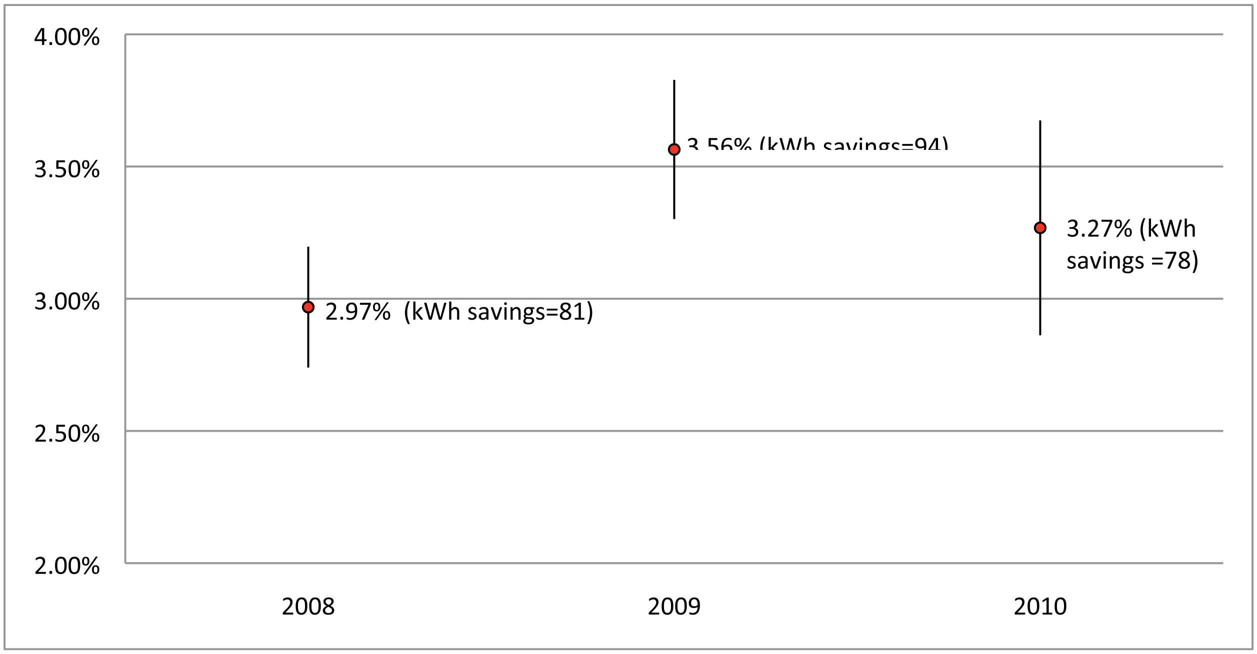
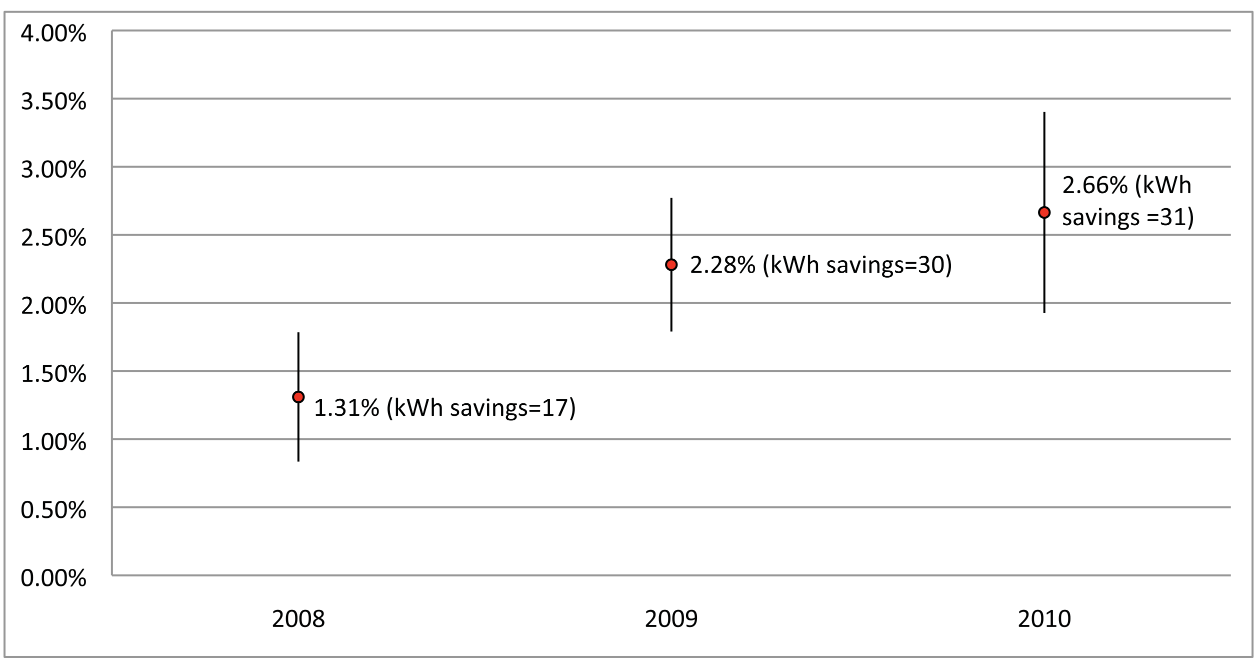


Figure 3.8. DID Estimates of July-August Average Household Percent Savings with 95% Confidence Intervals, with kWh savings indicated, *LC households (quarterly reports)*



B. Results of Linear Fixed Effects Regression (LFER) Analysis

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The difference between the estimated savings for high consumption households in summer 2009 and summer 2010 presented in Figures 3.1-3.2 and 3.7 can lead one to conclude that the effectiveness of the program is waning over time, and so we arrive at a cautionary note about DID analysis: because the basic DID statistic is not conditioned on variables that change over time, such as weather variables, it is not a good basis for evaluating persistence of program effectiveness, where we define program effectiveness as program savings after accounting for random fluctuations in factors that change over time, such as weather and the overall state of the economy. In other words, *program effectiveness reflects the behavioral fundamentals of the program*.

Consider, for instance, that the summer of 2010 was about 25% cooler than the summer of 2009. To the extent that the treatment effect is greater on hotter days –a quite reasonable hypothesis—the difference in the treatment effect between the summer of 2009 and 2010 can be explained without resorting to discussions about changes in behavioral fundamentals. LFER analysis permits the analyst to condition the treatment effect on a variety of variables that change over time, thereby providing insight about the explanation for relatively low program savings in Summer 2010, and more generally, long term trends in program savings.

We estimated the degree day model and extensions involving linear, quadratic, cubic, and quartic trends for both HC and LC households to get a broad sense of ramping and persistence in program savings. Models were fit to the 12-month pre-program period and the 29-month program period for which we had sufficient data (April 2008-August 2010). Regression results for these models are presented in Tables B.1-B.5 in Appendix B. For all models the shaded rows in the tables indicate regression terms that impact estimates of program savings. In the discussion below we use these models to first examine the long term trend in program savings, and to then take up the issue of fluctuations around the long trend due to interseasonal temperature fluctuations.

Long term trend in program savings

Using the LFER results for the degree day model and its polynomial trend extensions, we developed annualized savings trends –trends scaled up to annual average savings—by using average annual heating and cooling degree days per day in the estimate of the ADTE's in (5) and (8)-(10), and then multiplying the ADTE's by 365. These annualized trends are presented in Figures 3.9 and 3.10.[6] It must be remembered that the peaks and valleys in the polynomial trends in the figures do not necessarily reflect actual behavioral changes over time, but may instead reflect the attempt to capture the overall trend in program savings with flexible functional forms that are inclined to undulate. To correct for this possibility, we average the trends produced by the four polynomial specifications, with results presented in Figures 3.11 and 3.12, with annualized savings for the degree day model (no trend) for comparison. Results appear to indicate that program savings for HC households involves a ramp-up period of about 10-12 months followed by fairly constant annual savings of about 390-400 kWh, and that program savings for LC households continue to trend upward.

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[6] Average annual heating and cooling degree days used in the figures are those for Sacramento, CA as reported by the National Climate Data Center, NOAA-USDC at
http://www.ncdc.noaa.gov/oa/climate/online/ccd/nrmcdd.html
and http://www.ncdc.noaa.gov/oa/climate/online/ccd/nrmhdd.html .

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It is possible that the polynomial fits to the long-term trend for HC households is distorted by the attempt of the polynomial forms to capture the ramp-up period. With this in mind we re-estimated the four polynomial trend models for the program period 6-29 months—that is, we dropped the first 5 months of the program period from the analysis. Trend results for this model are shown in Figure 3.13, and averaging the trends generates Figure 3.14. These results support the conclusion of a ramp-up period of about 10-12 months, followed by an 18- month period to the end of the available data (September 2008 –August 2010) over which there is neither an upward nor downward trend in program savings. The steady-state annual savings appears to be closer to 380 kWh rather than the 390-400 kWh indicated in Figure 3.11.

In summary:

- *For HC households, program savings ramped up for 10-12 months and are now on trajectory of relatively constant annual savings of about 390 kWh per household;*

- *For LC households, program savings continue to trend upward.*

Temperature-related fluctuations around the long term trend

The foregoing analysis considers the long term trend in annual savings, with interseasonal, temperature-related fluctuations around the trend suppressed by using average annual heating and cooling degree days per day for the variables $HDDd_t$ and $CDDd_t$ in equations (5) and (8)-(10). We now turn to analyzing these fluctuations. For each of the coefficients β_3 and γ_3—the coefficients capturing the effect of $HDDd_t$ and $CDDd_t$ on program savings—we averaged coefficient estimates across the degree day model and the four trend models, and then used these averaged coefficient estimates with appropriate monthly degree day data to estimate the *actual effect* of temperature over the 29-month program period, and to predict the long-run average effect of temperature on program savings.[7] Figures 3.15 and 3.16 present the results of this exercise. The average monthly temperature-related savings reflect average annual heating and cooling degree days, and are the values used in the annualized trend analysis just presented. The estimates of actual temperature-related monthly program savings are based on actual heating and cooling degree days during the course of the program (April 2008-August 2010), and the horizontal axis is labeled to reflect the program period. Long-term average values are based on long run heating and cooling degree days, as reported by the National Climate Data Center, NOAA-USDC (see footnote 8 above). The figure generates the following conclusions:

- *Temperature-related savings are highest in summer;*

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[7] This averaging was done separately for the HC and LC household models. The coefficient estimates for β_3 and γ_3 were strongly significant in the degree day model and all four trend regressions, for both the HC and LC models. Moreover, because these coefficient estimates were fairly stable across the five models, the averaged estimates are reasonably close to the estimates in each of the equations. For instance, as seen in Tables A.1-A.5, the estimates of β_3 across the degree day model and the four trend models for HC households, were -.02729, -0.02674, -0.01989, -0.02111, and -0.01865, which averages to -.02274. The coldest month of the year, January, has a long term average value of HDD=580, and so the estimated program savings due to heating degree days in January varies from a high of 580·.02729=15.8 kWh for the linear trend, to a low of 10.8 kWh for the quartic trends, with an average estimate of 13.2 kWh.

- *Temperature-related fluctuations in program savings follow the same pattern for high consumption and low consumption households, with the savings for high consumption households scaled up.by a factor of about 2.5;*
- *Recent summers have been cool, with temperatures especially cool in summer 2010. This appears to largely explain the relatively low savings reported for HC households in summer 2010 compared to summer 2009 (see Table 3.1 and Figure 3.2). In particular, the cooler summer in 2010 compared to 2009 accounts for a difference of about 12 kWh in program savings.*

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Figure 3.9. Annualized Savings Trend for High Consumption (HC) Households

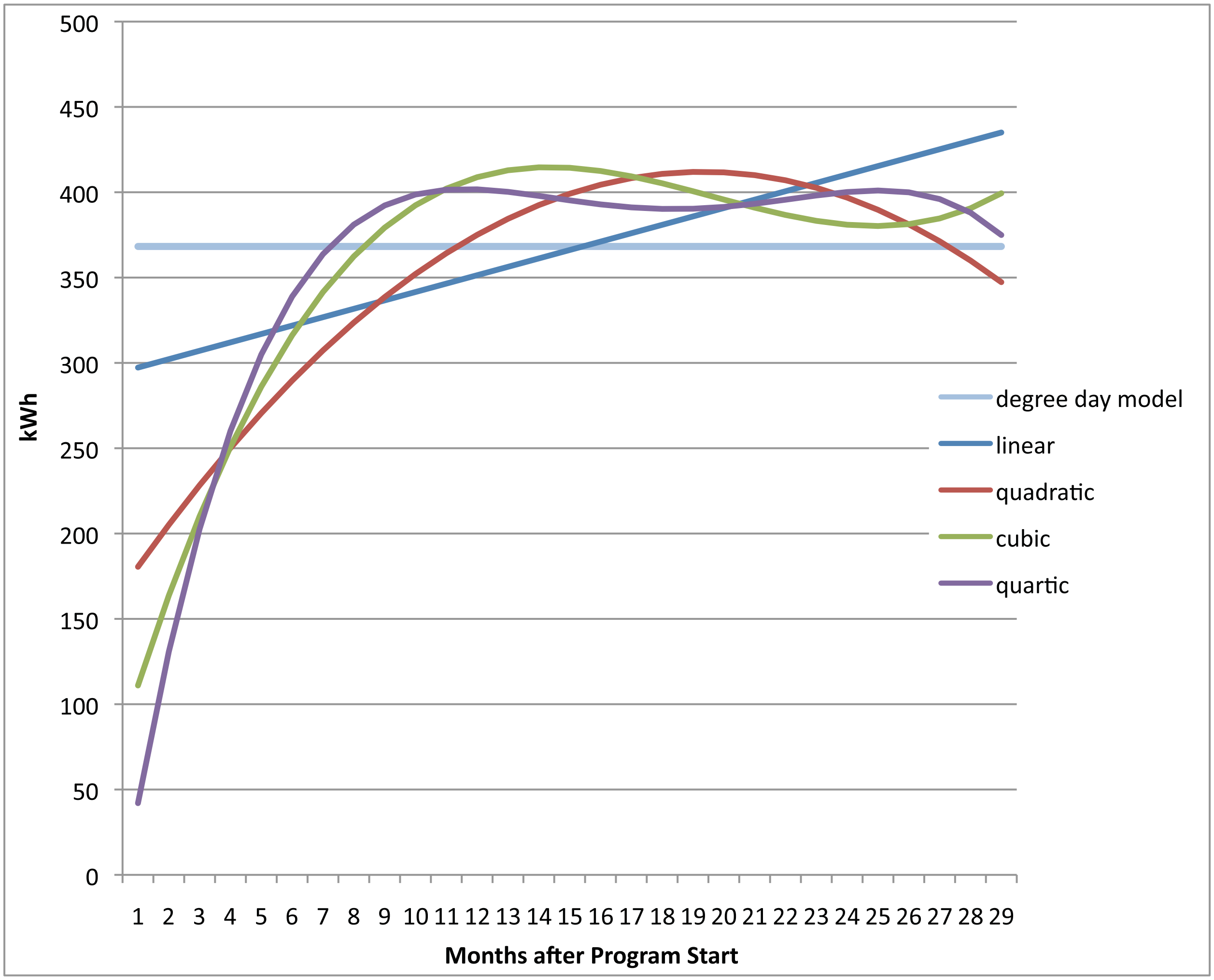

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Figure 3.10. Annualized Savings Trend for Low Consumption (LC) Households

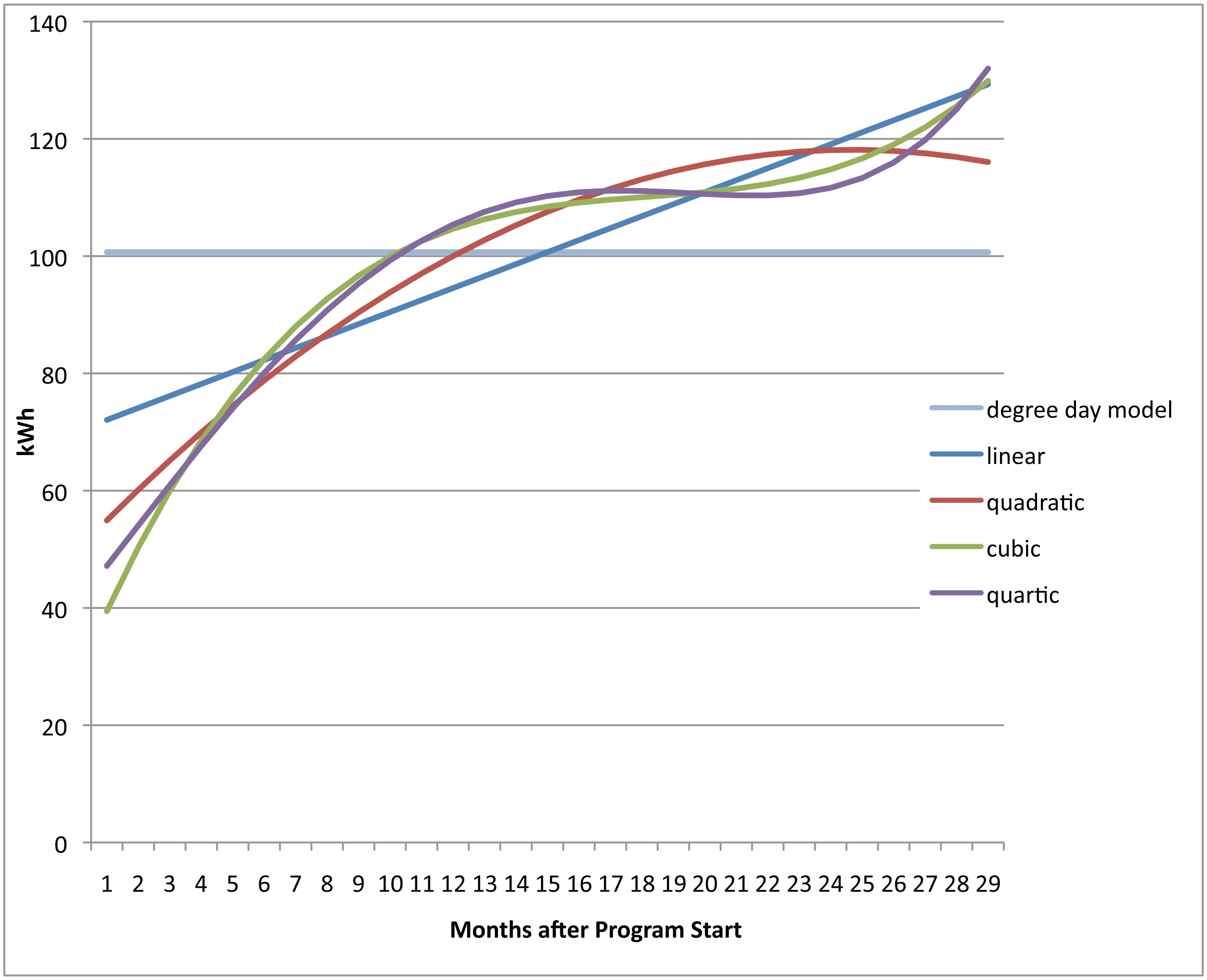

Figure 3.11. Annualized savings trend average, HC households

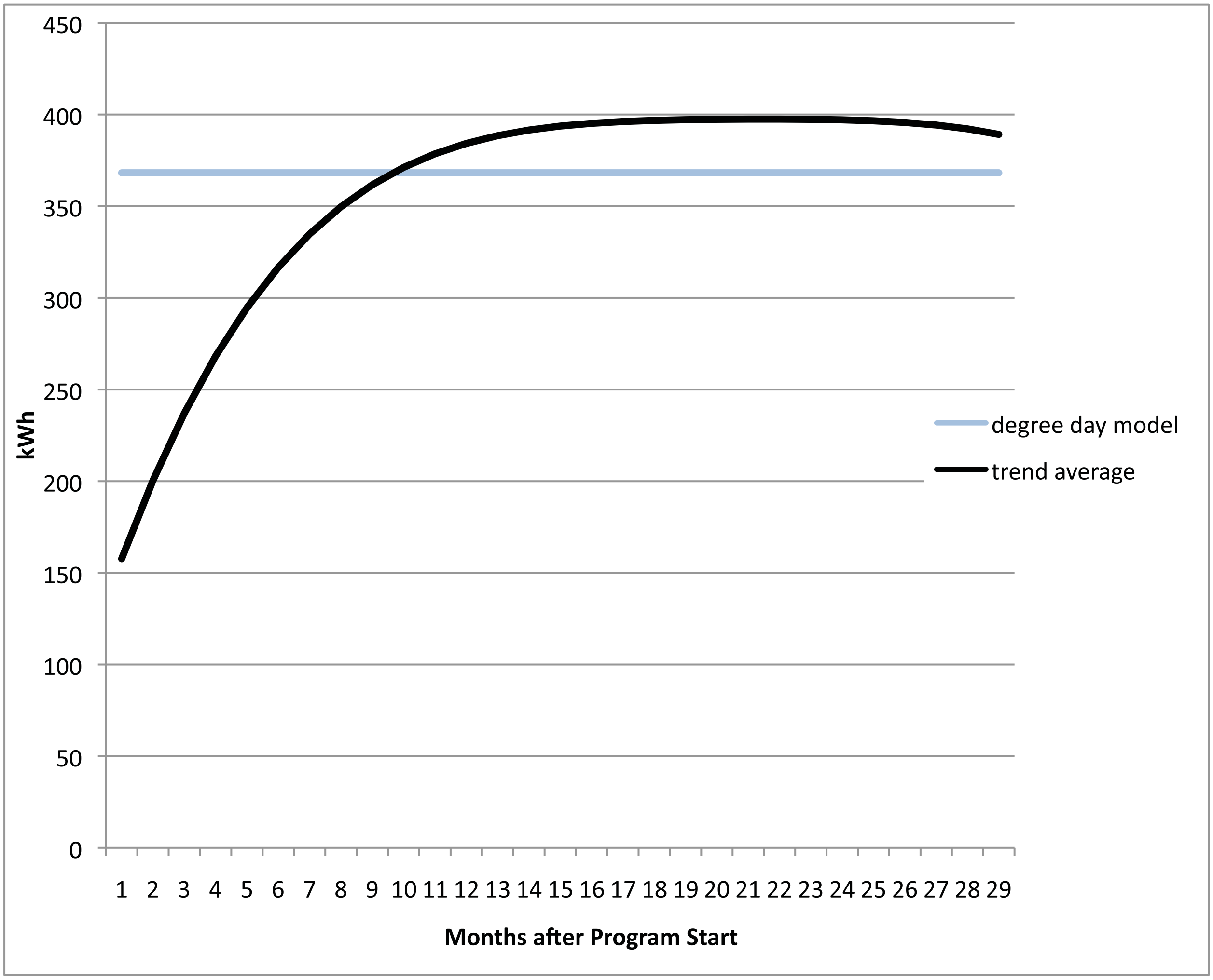

Figure 3.13. Annualized savings trend average, LC households

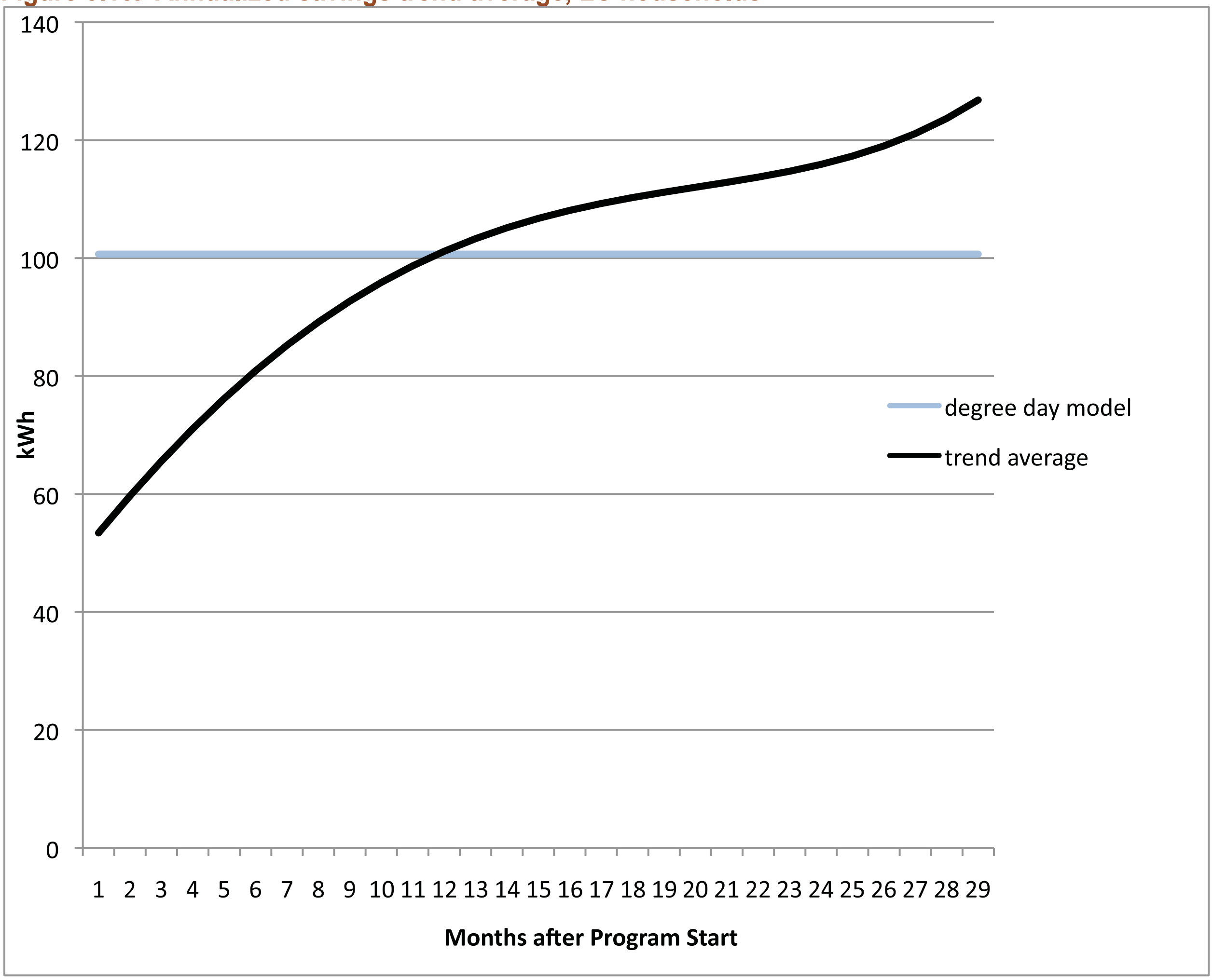

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Figure 3.13. Annualized savings trend after first 5 months of the program, HC households

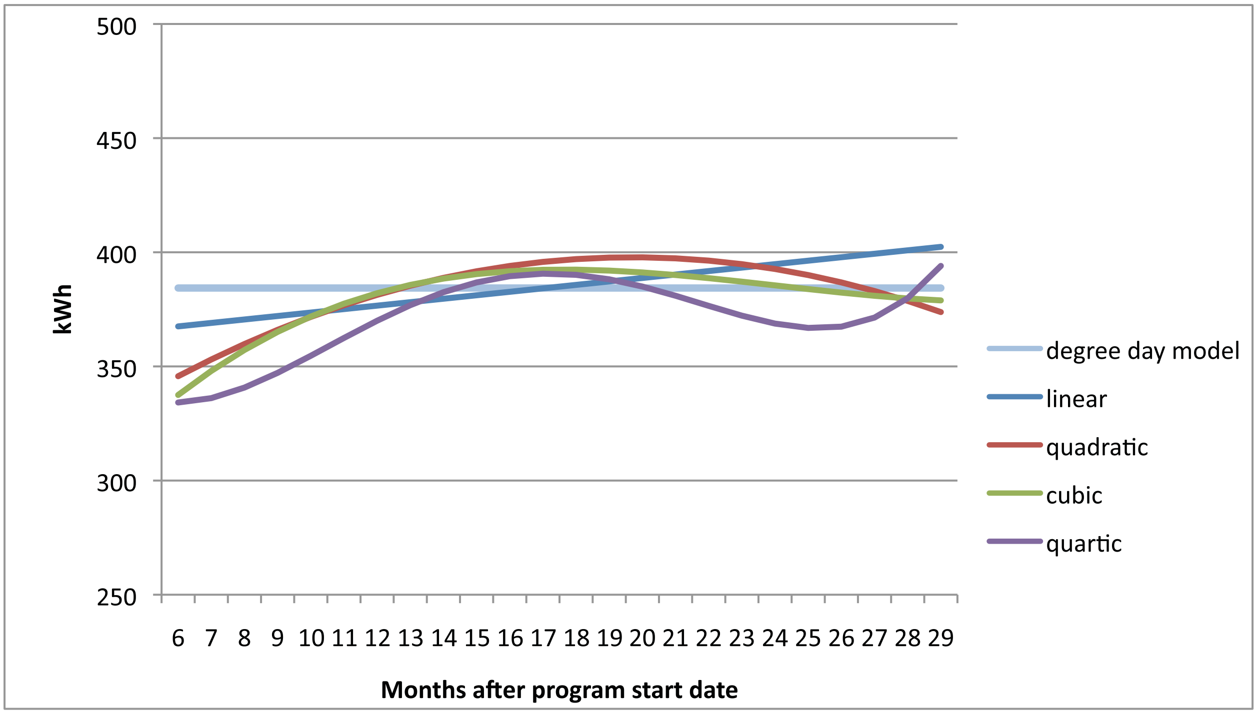

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Figure 3.14. Annualized savings trend average after first 5 months of the program, HC households

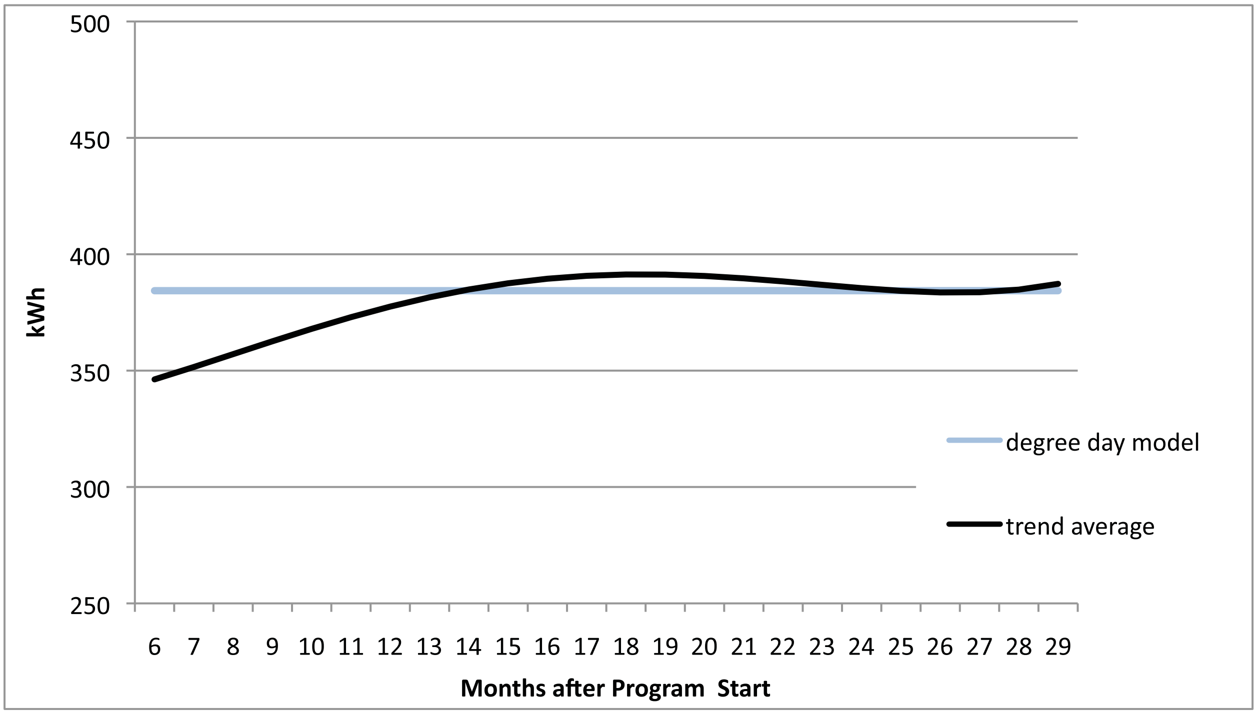

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Figure 3.15. Temperature-related monthly program savings, HC households

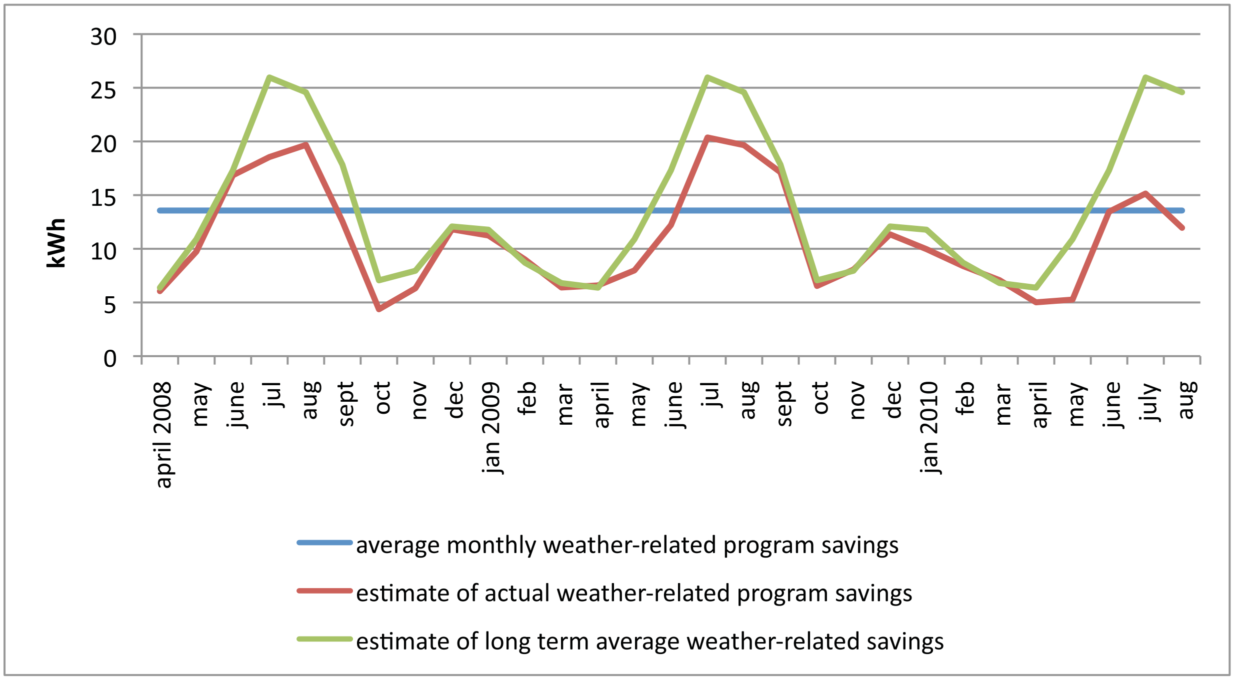
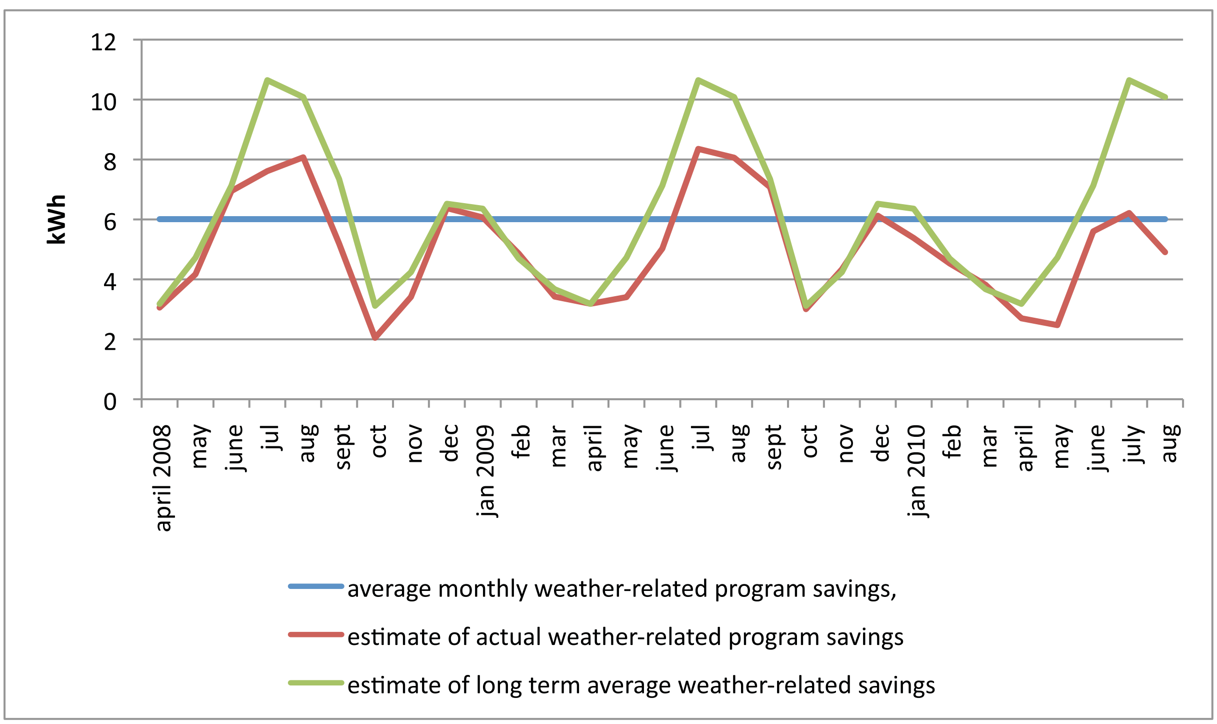


Figure 3.16. Temperature-related monthly program savings, LC households



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IV. Conclusion

The analysis presented in this report generates the following overall conclusions:

A. The program continues to generate savings

- Average savings in program Year 2 were 2.89% for high consumption (HC) households receiving monthly reports, and 1.70% for low consumption (LC) households receiving quarterly reports.
- Year 2 average household savings is 381 kWh for HC households and 104 kWh for LC households.
- Average household savings through the first 30 months of the program is 878 kWh for HC households and 234 kWh for LC households.

B. The trend for high consumption households

Program savings are characterized by temperature-driven seasonal fluctuations around a baseline trend. For HC households, the baseline trend ramped up through the first 10-12 months and has remained fairly constant since then:

- Average percent savings in program Year 2 are higher than in Year 1, 2.89% compared to 2.37%, which is a 22% increase in savings in the second year. The increase is statistically significant.
- Statistical analysis indicates that the long term trend for savings leveled off at about 10-12 months, and has remained constant since then. In other words, after the first year of the program the fundamental effectiveness of the program does not appear to have changed substantially.
- Statistical analysis supports a long term savings trend of about 380 kWh per year, approximately 2.9% per year.
- Additional analysis after the program has been in place for a full three years, with data for at least three occurrences of each season, should give a better indication of whether the long term trend in savings is indeed constant or instead showing signs of rising or falling.

C. The trend for low consumption households

For LC households, program savings continues to trend upward:

- Average percent savings in program Year 2 are higher than in Year 1, 1.70% compared to 1.25%, which represents a 36% increase in savings.
- Statistical analysis indicates that program savings continue to trend upward through the first 29 months of the program.

D. Program savings increase with electricity use

For both HC and LC households, program savings reveal strong seasonal effects, with savings highest in the seasons of highest electricity use, summer and winter. For instance, in Year 2 (spring 2009-winter 2010) the average kWh savings for HC households in the seasonal sequence spring-summer-fall-winter was 80-123-84-97 kWh. The same sequence for LC households was 13-36-20-33 kWh.

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The seasonality of savings is especially apparent in the pronounced rise in savings in the months of July and August. For HC households the percent savings for these months is 3.56% in summer 2009 and 3.27% in summer 2010. The difference between these percent savings is not statistically significant at any reasonable level of significance (the t-statistic on the difference is 1.2).

E. Graphical summary

Figures 4.1 and 4.2 present the trends in annual program savings for HC and LC households over months 6-29 of the OPOWER program. The figures abstract from seasonal fluctuations in program savings by setting heating and cooling degree days at their annual averages. The figures illustrate several of the points made above:

- For HC households, program savings appear to have remained constant on an annual basis after an initial ramp-up period of about 10-12 months; the tail end of the ramp-up period is apparent in months 6-12 of the figure. The long run annual savings of about 380 kWh is a savings of approximately 2.9% per year.
- For LC households, program savings continue to trend upward.

Figure 4.3 presents monthly fluctuations in program savings directly attributable to fluctuations in temperatures during the program period. The figure illustrates that:

- Program savings are highest in the summer and winter months, with the summer response especially pronounced for HC households;
- Fluctuations follow the same pattern for HC and LC households, with fluctuations for HC household scaled up by a factor of about 2.5 relative to LC households.

Figure 4.1. Trend in annual program savings, HC households, program months 6-29 (September 2009-August 2010).

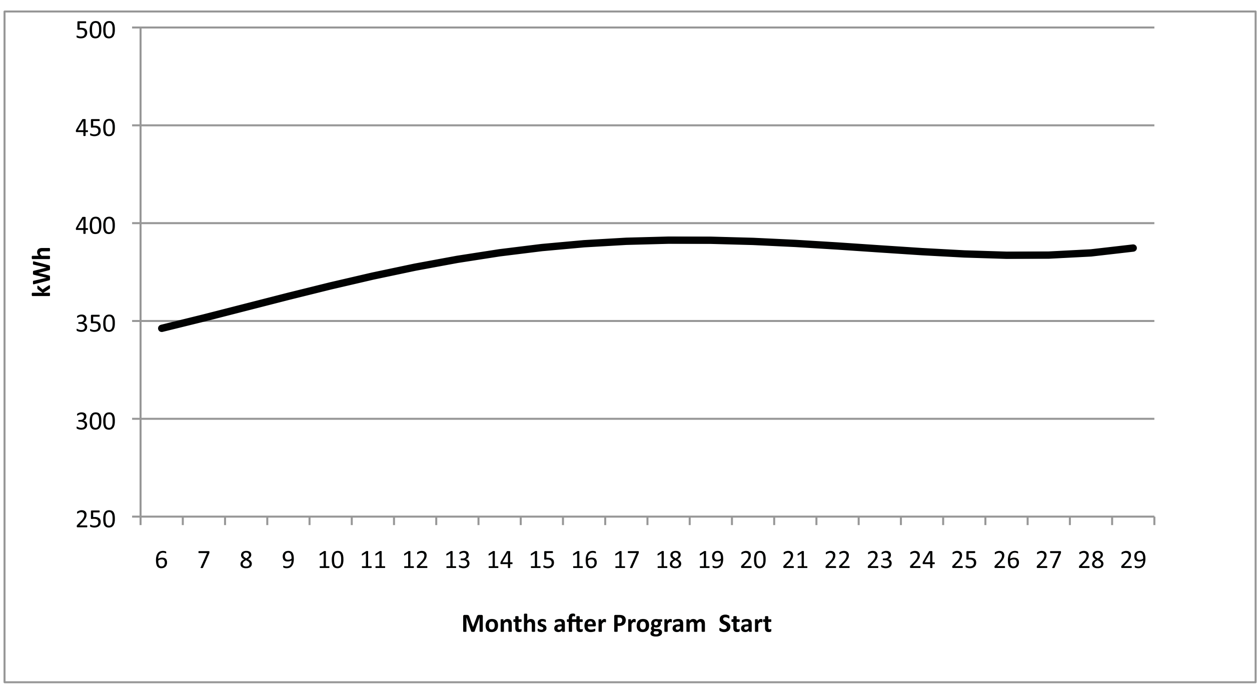

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Figure 4.2. Trend in annual program savings, LC households, program months 6-29 (September 2009-August 2010).

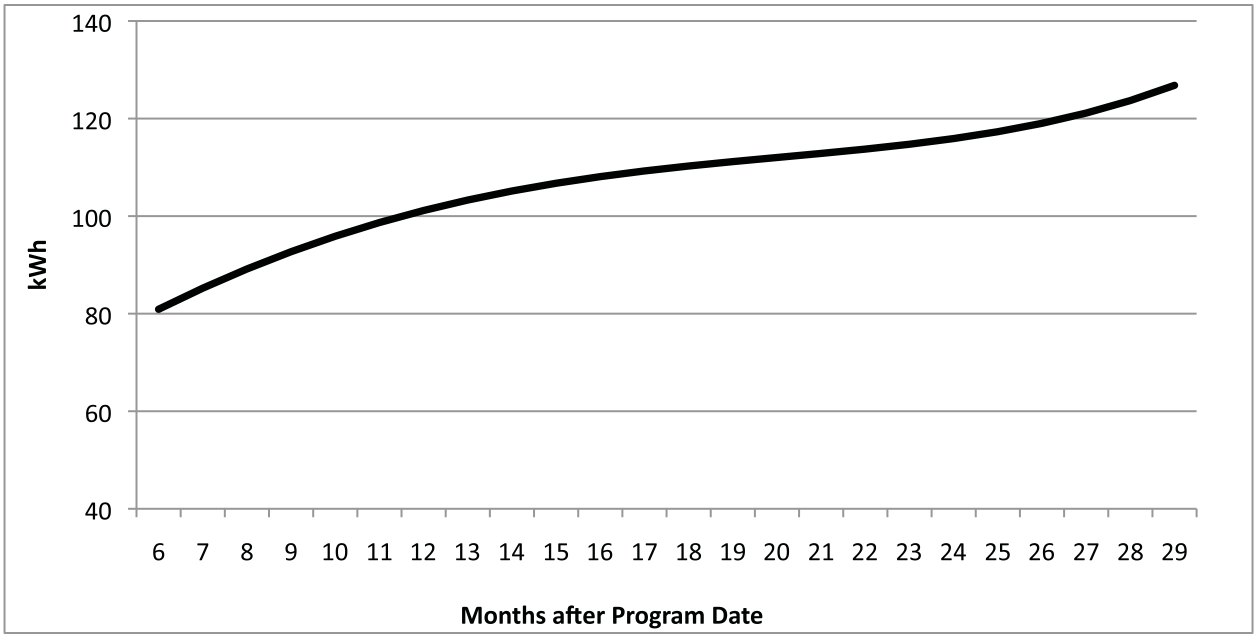
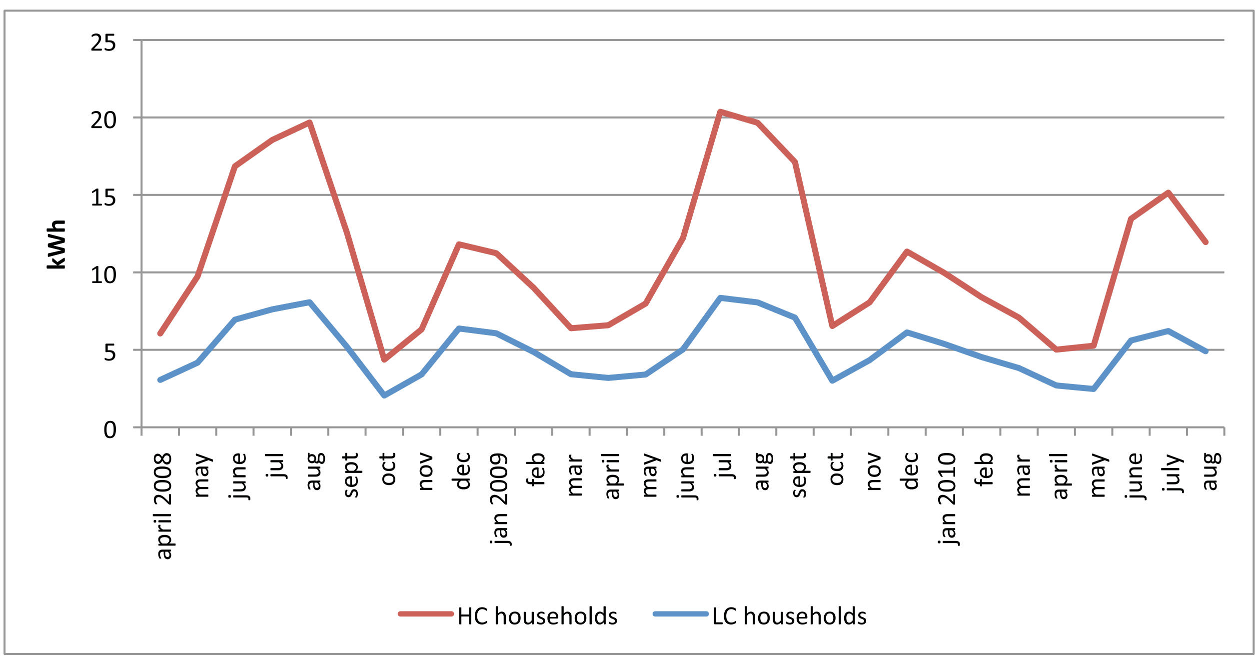


Figure 4.3. Estimate of temperature-related monthly program savings



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Appendix A. Baseline Statistics Used in Analysis

Table A.1. Baseline Statistics: Average Daily kWh Consumption, Heating Degree Days, and Cooling Degree Days, by Period[a]

Period	kWh Average Daily Consumptio n HC Control Households	kWh Average Daily Consumption HC Treatment Households	kWh Average Daily Consumption LC Control Households	kWh Average Daily Consumption LC Treatment Households	Heating Degree Days per Day	Cooling Degree Days per Day
First Year	37.35	35.87	16.60	16.43	7.32	2.18
Second Year	36.69	35.03	16.75	16.50	7.05	2.63
Summer 2008	44.16	42.51	20.61	20.48	0.11	6.65
July-August 2008	45.73	43.79	21.53	21.32	0.05	7.72
Fall 2008	33.98	32.28	15.02	14.75	4.51	1.83
Winter 2008-2009	39.79	38.24	16.97	16.80	17.45	0.00
Spring 2009	32.00	30.58	14.21	14.03	6.23	1.25
Summer 2009	41.96	40.10	19.91	19.58	0.07	6.83
July-August 2009	44.49	42.39	21.31	20.92	0.00	8.01
Fall 2009	35.07	33.20	15.94	15.64	5.71	2.81
Winter 2009-10	38.27	36.69	16.99	16.78	16.01	0.00
Spring 2010	30.75	29.38	13.86	13.66	8.25	0.24
Summer 2010	40.43	37.31	18.53	18.12	0.47	5.27
July-August 2010	40.43	38.46	19.23	18.74	0.05	5.48

aThe first year applies to bill dates in the period April 2008-March 2009; the second year applies to bill dates in the period April 2009-March 2010; spring season applies to bill dates in the interval March 15-June 14; summer season applies to bill dates in the interval June 15-September 14; fall season applies to bill dates in the interval September 15-Dec 14; winter season applies to bill dates in the interval Dec 15-March 14; July-August period applies to bill dates in the interval July 15-September 15.

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Appendix B. LFER Regression Results

Table B.1 LFER Analysis Result: Degree Day Model

Variables	Coefficient Estimates			
	High Consumption (HC) Households		**Low Consumption (LC) Households**	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.8913	338.41	0.3380	173.83
CDDd	2.8816	404.41	1.3812	263.60
Treatment*HDDd	-0.0027	-0.66	0.0089	2.93
Treatment*CDDd	-0.0384	-3.45	0.0056	0.69
Post	-0.4010	-8.59	0.2547	7.39
Post*HDDd	-0.0394	-11.03	0.0246	9.30
Post*CDDd	-0.3057	-35.02	-0.0801	-12.41
Treatment*Post	-0.5106	-6.98	-0.0778	-1.44
Treatment*Post*HDDd	-0.0273	-4.87	-0.0119	-2.85
Treatment*Post*CDDd	-0.0883	-6.47	-0.0329	-3.25

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Table B.2. LFER Analysis Results: Degree Day Model with Linear Trend

Variables	Coefficient Estimates			
	High Consumption (HC) Households		Low Consumption (LC) Households	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.89122	338.5	0.33807	173.88
CDDd	2.88097	404.47	1.38145	263.68
Treatment*HDDd	-0.00273	-0.66	0.00891	2.92
Treatment*CDDd	-0.03868	-3.48	0.00551	0.67
Post	0.12313	2.41	0.04192	1.10
Post*HDDd	-0.03871	-10.83	0.0246	9.29
Post*CDDd	-0.31576	-36.15	-0.07462	-11.54
PostTrend	-0.03214	-25.47	0.01293	13.27
Treatment*Post	-0.29446	-3.68	0.01482	0.25
Treatment*Post*HDDd	-0.02674	-4.78	-0.01189	-2.86
Treatment*Post*CDDd	-0.09189	-6.73	-0.03537	-3.49
Treatment*PostTrend	-0.01348	-6.79	-0.0056	-3.66

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Table B.3. LFER Analysis Results: Degree Day Model with Quadratic Trend

Variables	Coefficient Estimates			
	High Consumption (HC) Households		**Low Consumption (LC) Households**	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.89108	338.5	0.33794	173.81
CDDd	2.88007	404.47	1.38088	263.54
Treatment*HDDd	-0.0029	-0.66	0.00887	2.91
Treatment*CDDd	-0.0398	-3.48	0.00532	0.65
Post	0.33371	2.41	0.16569	3.86
Post*HDDd	-0.03343	-10.83	0.02761	10.25
Post*CDDd	-0.30978	-36.15	-0.07216	-11.14
PostTrend	-0.07777	-25.47	-0.01359	-3.10
$PostTrend^2$	0.00144	-25.47	0.000853	6.21
Treatment*Post	-0.01816	-3.68	0.05973	0.89
Treatment*Post*HDDd	-0.01989	-4.78	-0.01078	-2.55
Treatment*Post*CDDd	-0.08447	-6.73	-0.03441	-3.39
Treatment*PostTrend	-0.07302	-6.79	-0.01524	-2.22
$Treatment*PostTrend^2$	0.00189	-6.79	0.000309	1.43

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Table B.4. LFER Analysis Results: Degree Day Model with Cubic Trend

Variables	Coefficient Estimates			
	High Consumption (HC) Households		**Low Consumption (LC) Households**	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.89292	339.43	0.33912	174.46
CDDd	2.89298	406.25	1.38616	264.46
Treatment*HDDd	-0.0032	-0.78	0.00875	2.87
Treatment*CDDd	-0.04182	-3.76	0.00484	0.59
Post	-1.83376	-25.82	-0.6147	-11.47
Post*HDDd	-0.02751	-7.58	0.02852	10.59
Post*CDDd	-0.3281	-37.44	-0.07662	-11.83
PostTrend	0.62417	42.00	0.24206	21.23
$PostTrend^2$	-0.05213	-49.00	-0.01893	-22.91
$PostTrend^3$	0.00114	51.05	0.000426	24.28
Treatment*Post	0.28938	2.60	0.1217	1.45
Treatment*Post*HDDd	-0.02111	-3.71	-0.0109	-2.58
Treatment*Post*CDDd	-0.08247	-6.02	-0.03448	-3.39
Treatment*PostTrend	-0.17145	-7.34	-0.03519	-1.97
$Treatment*PostTrend^2$	0.00941	5.63	0.00187	1.44
$Treatment*PostTrend^3$	-0.00016	-4.56	-3.4E-05	-1.24

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Table B.5. LFER Analysis Results: Degree Day Model with Quartic Trend

Variables	Coefficient Estimates			
	High Consumption (HC) Households		**Low Consumption (LC) Households**	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*
HDDd	0.89238	339.11	0.33939	174.38
CDDd	2.88935	404.76	1.38734	263.79
Treatment*HDDd	-0.00356	-0.87	0.00881	2.89
Treatment*CDDd	-0.04436	-3.98	0.00515	0.62
Post	-1.43528	-16.03	-0.73206	-10.66
Post*HDDd	-0.0241	-6.59	0.02734	10.03
Post*CDDd	-0.32361	-36.84	-0.07761	-11.96
PostTrend	0.41861	13.15	0.30254	12.16
$PostTrend^2$	-0.0253	-6.61	-0.0269	-8.88
$PostTrend^3$	-0.00016	-0.88	0.000816	5.69
$PostTrend^4$	2.06E-05	7.30	-6.3E-06	-2.74
Treatment*Post	0.58517	4.16	0.08913	0.83
Treatment*Post*HDDd	-0.01865	-3.25	-0.01121	-2.62
Treatment*Post*CDDd	-0.07949	-5.79	-0.03477	-3.42
Treatment*PostTrend	-0.32305	-6.45	-0.01843	-0.47
$Treatment*PostTrend^2$	0.02917	4.85	-0.00033	-0.07
$Treatment*PostTrend^3$	-0.00111	-3.96	7.28E-05	0.32
$Treatment*PostTrend^4$	1.51E-05	3.42	-1.7E-06	-0.48

Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage

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Abstract: By providing feedback to customers on home electricity and natural gas usage with a focus on peer comparisons, utilities can reduce energy consumption at a low cost. We analyze data from two large-scale, random-assignment field experiments conducted by utility companies providing electricity (the Sacramento Municipal Utility District (SMUD)) and electricity and natural gas (Puget Sound Energy (PSE)), in partnership with a private company, Positive Energy/oPower, which provides monthly or quarterly mailed peer feedback reports to customers. We find reductions in energy consumption of 1.2% (PSE) to 2.1% percent (SMUD), with the decrease sustained over time (seven months (PSE) and twelve months (SMUD)).

Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage

I. Introduction

In this paper we analyze two field experiments conducted on a total of approximately 75,000 household customers of two utilities, the Sacramento Municipal Utility District (SMUD) and Puget Sound Energy (PSE). These utilities, in partnership with a private company, Positive Energy/oPower, randomly assigned a subset of these households to periodically receive mailed reports comparing their energy usage to that of nearby neighbors in similarly sized houses. We find that households receiving Positive Energy/oPower's reports make significant and lasting reductions in their energy consumption.

Studies that have tested the impact of peer comparisons on conservation have had mixed results. For example, Goldstein, Cialdini, and Griksevicius (2008) have found that social norms can increase towel reuse by hotel guests. Yet, in a literature review of the effect of feedback on home energy consumption, Fischer (2008) notes that of the dozen studies that she reviews that test the impact of comparisons to others, none had shown an effect. She attributes the failure to the "boomerang" problem, where informing individuals of typical peer behavior inadvertently inspires those who have been *under*-estimating the prevalence of an activity to increase the unwanted behavior. Cialdini, Kallgren, and Reno (1991) argue that combining injunctive norms (norms that express social values rather than actual behavior) with descriptive norms can neutralize the boomerang effect. Schultz, Nolan, Cialdini, Goldstein, and Griskevicius (2007) conducted a randomized field study in San Marcos, California, of the effectiveness of social norms messaging (alongside energy-saving tips) to reduce home energy consumption. They found that combining the descriptive and injunctive messages (in this case, the emoticons ☺ and ☹) lowered energy consumption and reduced the undesirable boomerang effect.

The Positive Energy/oPower experiments build on the findings of the San Marcos study. As in the San Marcos study, the Positive Energy/oPower reports use descriptive norms as well as injunctive norms, such as ☺ emoticons, to reduce consumption and in order to counteract the boomerang effect. The Positive Energy/oPower experiments reported here, however, go beyond the San Marcos experiment in a number of ways. First, the Positive Energy/oPower experiments have a significantly larger sample size than in San Marcos, which included 290 households vs. 35,000 in the SMUD study and 40,000 in the PSE study. Second, the Positive Energy/oPower studies also allow us to test multiple new aspects of the dynamics of energy use feedback:

- **Measuring longer term impacts**. Whereas the San Marcos study's observation period was only one month, the SMUD and PSE experiments have twelve and seven months of data, respectively.
- **Measuring daily impacts**. Unlike the San Marcos study, the PSE experiment gives access to daily energy readings.
- **Measuring impacts on both electricity and natural gas**. The PSE experiment tested the effect of feedback on both electricity and natural gas usage, allowing a fuller picture of household energy use.
- **Measuring impacts of different message frequencies (quarterly vs. monthly), different report content, and different envelope sizes.**

Moreover, the Positive Energy/oPower experiments were conducted using a more realistically scalable intervention. Instead of mailed reports, the San Marcos study used hanging doorknockers with hand-drawn emoticons. Together, the SMUD and PSE experiments provide compelling evidence that properly framed peer comparisons can predictably lower energy consumption, particularly of the highest energy using households.

II. SMUD Experiment

Experimental design. The SMUD messaging experiment began in April 2008 and is still ongoing; the results presented in this paper cover the period from April 2008 through April 2009.[1] The sample includes 85,000 households who are customers of SMUD. To select participants, Positive Energy/oPower filtered by census tract within SMUD's footprint to maximize the number of single family homes with more than twelve months of billing history,

[1] All the data in this paper, including data originally obtained from the utilities themselves as well as from third parties, was generously provided to the authors by Positive Energy/oPower. SMUD has contracted with ADM & Associates to independently assess the success of the program. In addition, Positive Energy/oPower engaged Summit Blue to do its own evaluation of the SMUD result in May 2009. PSE plans to select a third party in October 2009 to conduct program measurement and verification services.

that were on standard rate plans (non-medical rate, non-photovoltaic), and that had a matching parcel record with details about the home, such as house size and value.

Once participants were selected, the randomization process used “batch” assignment: homes were randomly assigned to the treatment and control groups in 959 batches of census blocks. These “batch blocks” consist of 50 to 100 homes. 35,000 households were assigned to the treatment group, and 50,000 were assigned to the control. Positive Energy/oPower used this assignment methodology to increase the likelihood that neighbors would receive reports and have the opportunity to discuss the reports with each other, thereby increasing the motivation for taking actions to reduce home electricity consumption. The batch approach did have a drawback, however, in that treatment and control groups differed on some pre-treatment attributes.

All members of the treatment group received home energy reports on a periodic basis. Each home energy report contains four key personalized components: 1) Current period neighbor comparison: A bar chart comparing the household’s recent electricity use to a group of comparable neighbors and “efficient neighbors,” with both normative and injunctive messages designed to motivate action; 2) Twelve-month neighbor comparison: A chart comparing the household’s electricity usage to its comparable neighbors and “efficient neighbors” over the last twelve months; 3) Personal historical comparison: A section comparing the household’s usage in the current year by month with the same months from the previous year; 4) Targeted energy efficiency advice: tips selected based on the household’s energy use pattern, housing characteristics, and household demographics. All reports were printed in color on a single 8½" x 11" sheet of paper. Examples of the elements of the front page of this report are included in Appendix A3a and Appendix A3b.

The 35,000 treatment households were then assigned to different sub-treatment groups that varied the intervention. Some of the assignments were random, while others depended on household characteristics. All households (test and control) were randomly assigned to one of two different report template groups and one of two different envelope groups. The two report template groups were “graphical” and “narrative.” Both templates included the same core elements, including graphs with feedback information, but the narrative version (shown in Appendix A3a and A3b) included a blurb of text explaining the charts, reinforcing the normative messages, and highlighting tips on how to save energy (including both mentioning tips in the blurbs and pointing the reader toward the personalized tips section on the back of the report).

The two envelope types tested included a standard business “#10” envelope (similar to the envelope used to deliver SMUD customer bills) and a larger 6" x 9" envelope. Envelope size did not affect the envelope content, which was always printed on 8½" x 11" paper; but folded differently to accommodate the different envelope sizes.

Some elements of the treatment varied based on household characteristics. Households were assigned to receive the reports either monthly or quarterly based on historical usage levels: the 25,000 households with higher consumption levels were assigned to the monthly frequency group, while the 10,000 households using less energy (< 21.85 kWh/day) were assigned to receive the report quarterly. Households were also assigned to various tip segments based on home characteristics (i.e. presence of a pool), which allowed for characteristic-contingent targeting of energy efficiency messages.

SMUD provided the basic data on energy consumption, including historical billing information dating back to January 1, 2006 (over two years before the beginning of the treatment in April 2008). Data on household parcel characteristics (such as square footage and home values) comes from the Sacramento County Assessor’s Office.[2] Household demographic data (such as income level and length of residence) came from private direct marketing and data aggregation service databases.

SMUD Results. Appendix A1 investigates whether the sample is well-balanced between the control and treatment groups. Since the randomization occurred at the census level, there were statistically significant differences in some pre-treatment variables. For example, the households in the treatment group on average were 16 square feet smaller and used .3 kWh per day more in 2006 than the average control group households. A parallel analysis (also reported in Appendix A1) of the sub-randomization of envelope size and the graphical/narrative template shows that the data was well-balanced between these groups.

Households in the treatment group that complained about receiving the Positive Energy/oPower reports or who asked to stop receiving the report were allowed to opt out of the treatment. Only 2% of the treatment group opted out of the experiment. The following regressions, which retain these observations and which only control for pretreatment variables,

[2] The heating fuel type was derived from the customers’ rate codes as SMUD offers lower rates to households with electric heat.

should be interpreted as "intent to treat" effects. Unreported treatment on the treated (IV) estimates were of similar in size and significance. In addition, similar proportions of treatment and control households (8% and 7%, respectively (p. = .10)) closed their SMUD accounts due to moving after the experiment began.

Figure 1 reports the results from monthly regressions on approximately 83,500 household observations where the log of monthly average kWh/day was regressed on a treatment group indicator and a constant. As shown in Figure 1, the treatment group's energy consumption (relative to the control group) moved erratically before the start of the experiment (indicated by a vertical line marking April, 2008). For example, the treatment group used more electricity than the control group in February 2007 and less in June 2007, and these differences were statistically significant. Still, even before other factors are controlled for, there was a significant drop in energy usage for the treatment group relative to the control for all the months following the initial report mailing.

To account for factors besides the reports that may be driving the change in energy usage, we control for house characteristics (square feet, age of house, presence of pool or spa, house value, gas user, census tracts), household demographics (energy usage in 2006, length of residence at particular house, number of residents, income, age, affluence), and the number of cooling degree days and heating degree days[3]. Figure 2 shows that after controlling for these characteristics there was no systematic difference in energy usage between the treatment and control groups. With the exception of one month in the pretreatment stage, the difference between the energy usage of the control and treatment groups is statistically insignificant, straddling 0%. After the first reports are arrived around April 15, 2008, we observe a significant drop in the electricity consumption of treatment households relative to control households, on the order of 1% in May 2008. The rapidity of this decline suggests that the reductions may be driven by more "behavioral" changes (such as turning off lights in empty rooms) rather than "durable" changes (such as caulking or replacing inefficient appliances). There is a steady decline until August 2008, where the treatment group saw a reduction in electricity usage by more than 2.5%. The gap between the usage levels of the control and treatment groups then narrows in the fall

[3] Cooling degree days and heating degree days are based on a base temperature of 65 degrees. For example, a day with an average temperature of 68 degrees will count as 3 cooling degree days. Similarly a day with an average temperature of 62 degrees will count as 3 heating degree days.

months (Sept. 2008 – Nov. 2008), though the reductions made by the treatment group are still significantly negative. After November 2008 the effect of the treatment grows in all months except April 2009, with the greatest reduction in electricity consumption since the beginning of the experiment (greater than 2.5%) occurring in March 2009, almost a year after the study first began.

To simultaneously investigate the impact of treatment across different months, we "stacked" the house-month data and again regressed the log of average monthly kWh/day for individual households on the controls reported in Table 1 (calculating standard errors by clustering on household IDs). The interaction between treatment and the variable named "After first mailing (April '08)" captures the effect of being in the treatment group after the start of the experiment. The average effect of the treatment on energy reduction is significant and robustly estimated in Table 1 at about 2.1%, with or without ancillary controls.

To understand the impact of template styles and envelope size combinations, we interacted these four variables with the treatment effect (Treatment x After first mailing) in a regression with the full controls from Table 1. As shown in Figure 3, the graphic template sent in a #10 business envelope reduced energy usage significantly more (nearly 3% relative to the control group) than the other three combinations (each less than 2%). More exploration is needed to determine why this combination of envelope size and template type had a stronger effect. One possible factor is that the #10 business envelopes resemble the envelopes in which SMUD sends its monthly bills, which may have inspired more individuals to open and read the communication. Figure 4 reports the treatment effects separately for households who received the reports monthly or quarterly from a parallel regression with full controls and interacting the treatment effect with monthly and quarterly indicators. Because lower (higher) energy using households were non-randomly assigned to receive reports quarterly (monthly), it is not surprising that monthly recipients reduce their energy consumption by 2.35% while quarterly recipients reduced their energy consumption by about 1.5%. As quarterly recipients had lower energy use to begin with, they likely had fewer opportunities to easily reduce kWh.

We also investigated whether the treatment effect varied for households with differing demographics. To capture the effects of wealth, we used house value as a proxy. Figure 5 reports the results of interacting the treatment effect with house value quintile indicators in a regression with full controls. Every house-value quintile of the treatment group used statistically less electricity than the control group; however the three lower-value quintiles had a reduction greater than the average of 2.1%, while the two higher quintiles saw a decrease less than the average.

We also investigated whether there were different treatment effects for households with different levels of pretreatment energy usage adjusted by house size. We created deciles of pretreatment energy usage per house square foot which was calculated using the usage fifteen months prior to experiment, and again interacted these indicators with the treatment effect in a regression with full controls. Figure 6 shows that households with larger pre-treatment usage generally experienced larger percentage reductions from receiving the reports. Reductions reported are relative to households from the same decile in the control group. In fact, the treated households in the two lowest deciles of pretreatment energy users increased their energy usage. It is possible that some of this phenomenon was driven by the fact that the households learned that their peers were consuming more electricity, in what Cialdini, Kallgren, and Reno (1991) have called the “boomerang” effect. The presence of a boomerang effect contradicts the findings Schultz, Nolan, Cialdini, Goldstein, and Griskevicius (2007) in the San Marcos study, where lower-consuming households did not increase their energy usage. This boomerang effect is not a necessary drawback of the treatment, however, as any program using peer feedback reports can always omit sending reports to the lowest-consuming households. In this case, the boomerang effect was overwhelmed by enhanced energy conservation in the other eight deciles. The highest energy users reduced their energy consumption by nearly 7% relative to high energy users who did not receive the report. It is not surprising that the households with higher historic usage per square foot should see a larger impact from the reports, since they were more likely to receive a message that they used more energy than their neighbors and were more likely to have discretionary energy use that was easy to reduce.

Table 2 estimates the potential yearly impact of the reports on both dollars saved and energy conservation if SMUD were to send the reports to all of the households in its customer base. At an average reduction of 2.35% for monthly recipients, the reports would reduce consumption 211 kWh per year per household for a total savings of about $31 a year per household (figures are based on SMUD system-wide average usage, which is about 2,000 kWh per year lower than the average for households in the experiment). Quarterly recipients would decrease their energy use by 130 kWh per year for a total annual savings of $13. If the nearly 593,000 households in SMUD’s customer base received reports using the same formula by which SMUD treatment households were assigned to monthly or quarterly reports, we could expect to see a reduction of over 110 million kWh in a year—the energy equivalent of saving over 9 million gallons of gas. SMUD customers would save over $15.2 million on their energy bills under the current SMUD rate plan. For every mailing in SMUD's customer base, $2.57 would be saved for monthly recipients, and $3.29 for quarterly. Since, as shown in Figure 6, higher energy users made significantly larger reductions in energy, it is likely that that targeting reports at only higher energy consumers would be particularly cost effective. By our analysis, SMUD could achieve a significant environmental impact by sending reports to all of its customers. The reports would save the equivalent of nearly 80,000 metric tons of carbon emissions. Quarterly reports produce a bigger energy saving per mailing (the equivalent of 1.43 and 2.64 gallons of gasoline per mailing for monthly and quarterly reports respectively).

Including report information with the regular bill may make the feedback even more cost effective. However, more research is needed into this question. It remains an open question whether including the reports in the bill would in fact reduce production costs, as such integration may require significant investments to change current legacy billing systems, which are typically in black and white and do not allow for extensive customization and graphics. Secondly, more research is needed to determine whether reports integrated into bills have the same level of impact on conservation. Similarly, researchers should investigate the effectiveness of electronic forms of delivery (such as email), which can further increase cost savings. Although such forms of delivery are likely to impact fewer households than direct mail for the time being, they promise significant production cost savings. Another approach to increasing the cost effectiveness of feedback reports would be to only send reports to households where there was not a danger of a "boomerang effect" (here, the lowest two deciles of pretreatment energy users).

III. PSE Experiment

Experimental design. In October 2008 Puget Sound Energy (PSE) and Positive Energy/oPower launched another energy feedback report experiment in King County, Washington. There were three major differences in program design between the SMUD and PSE studies: first, the reports encompassed both electricity and natural gas, allowing for a fuller picture of what is happening to households' energy use; second, the study included a randomized test of report frequency (monthly or quarterly), and did not test envelope size or template type; and third, the study used household-level randomization, which was more robust than the batch-level randomization used in the SMUD study.

The PSE experiment consisted of approximately 84,000 homes randomly assigned to control and treatment groups. These homes were chosen from PSE's 1.3 million residential customers who met the following criteria:

- Single family homes located in King County, WA
- Exactly one active electric account and one active gas account with PSE
- History for both gas and electric accounts dating to January, 2007
- Matched parcel record available from the King County Assessor's data
- Not identified by the King County Department of Assessments as having solar heat

This filter created a pool of approximately 100,000 households that were eligible to participate in the program. Additional exclusions were made to eliminate homes with distant neighbors or with unusual home sizes (so that neighbor comparisons would be more meaningful) and homes that used relatively little energy (less than approximately 80 MBTU). In order to test the effect of frequency of the reports on home energy consumption, households were also randomly assigned to receive the report on a monthly or quarterly basis in the ratio of 3:1. Unlike in the SMUD case, the PSE reports all used the same template and standard-business envelope size.

The PSE reports were based on the more effective "graphical" template deployed in the SMUD study. Sample elements from the front page of this report are included in Appendix A4a and A4b. However, the PSE report included energy information regarding both electricity and natural gas consumption. In addition to two charts tracking the last twelve months of households kWh and therm consumption relative to nearby neighbors in similar size homes, the template began with a combined energy cost (CEC) comparison to neighbors.[4]

[4] The combined energy cost is an estimate of the cost of electricity and gas used by the household. On the reports the combined energy cost was reported in terms of a price-weighted index (PWI), where PWI =12.51*therms + kWh. The factor 12.51 represents the kilowatt-equivalent price of one additional therm for a PSE customer. An estimate of the combined energy cost (CEC) can then be found by multiplying the PWI by the approximate price of one kWh, 8 cents. The combined energy cost does not exactly reflect the relative costs to the households because the actual pricing formula took into account other factors (e.g., fixed costs).

PSE Results. Appendix A2 shows that the randomization was successful in producing treatment and control households with similar pre-treatment attributes. The table does reveal some statistically significant differences between the randomly assigned monthly or quarterly groups, but the raw differences in levels was not substantial (for example, in 2007 the average kWh per day was 30.2 and 30.5 for the monthly and quarterly households respectively). Only 1% of the treatment group opted out of receiving the reports, which, as in the SMUD experiment, suggests that the following intent to treat estimates will be nearly identical to treatment on the treated effects. About 2% of both the control and treatment households closed their accounts during the experiment because they moved.

Figures 7a and 7b report the results of regressions of the log of monthly average kWh per day and therms per day usage on a treatment indicator and a constant. Unlike SMUD, where census-tract level randomization created some substantial pre-experiment differences between treatment and control households, the PSE data show no substantial differences in pre-experiment usage. All differences between the control and treatment groups for pre-experiment usage, as expected, were statistically insignificant and close to 0%. As Figures 7a and 7b show, however, the treatment households reduced their use of both electrical and natural gas energy relative to the control households in November 2008, after the reports were sent out first on October 20, 2008. As in SMUD, the rapidity of the decrease in electricity use may indicate that the reductions in energy may flow largely from behavioral rather than durable changes.

Table 3 displays the results of stacked monthly regressions (analogous to the SMUD regressions in Table 1) on approximately 1.4 million household-month observations. The regressions are run on the log of three measures of energy use: average monthly kWh per day, average monthly therms per day, and the combined energy cost (CEC). As in the SMUD Table 1, we report the results of parallel regressions with and without controls for house demographics (such as square footage, age of house, house value), household demographics (such as past energy usage), month, and cooling degree days and heating degree days. As with the SMUD data, the estimated treatment effects are quite robust to the inclusion of ancillary controls. On average, households in the treatment group reduced kWh usage by 1.2%, therm usage by 1.2%, and a combined price-weighted usage by 1.1% compared to the control group. One potential explanation for why this figure is lower than the SMUD average is that the experiment has been running for a shorter time. There is evidence, as shown in Figures 7a and 7b (discussed below), that the effect may continue to increase.

One advantage of this experiment is that PSE collects daily data on energy usage, with the aid of an automated meter read system called CellNet. Figure 8 reports the results of a regression (with the Table 3 controls) of household-day energy usage where the treatment variable from Table 3 (Treatment x After first mailing) was interacted with day of week indicators. The figure shows that the lion's share of treatment impact, 38%, comes from Sunday and Monday (12:00 AM Sunday morning to 11:59 PM Monday night). It may be that the energy savings is even more tightly concentrated in the weekend, with the bulk of the "Monday" savings occurring during the night between Sunday and Monday. For example, if a person decides to turn her thermostat down on Sunday, she may leave whatever setting she has chosen on all night. The evidence that the bulk of the savings is happening on two contiguous days roughly overlapping with the weekend suggests that the primary impact of the energy reports may not be driven by durable conservation efforts, but is instead from increased mindfulness of energy consumption on the weekends. On the other hand, it may be that increased savings on the weekends could be the result of durable, one-time actions as well. For example, if an individual buys a new energy-efficient washing machine, and she does the bulk of her laundry on the weekends, she would show the greatest percentage drop in energy on the weekends.

As already discussed, in the SMUD experiment, as shown in Figure 4, those who received the report monthly saved more electricity than those who received it quarterly. However, in SMUD only the lower (pre-treatment) energy-using households were assigned to the quarterly treatment group, leading to the possibility that the smaller estimated quarterly treatment effect was driven by lower pre-treatment energy usage. In the PSE experiment, however, with randomized monthly and quarterly recipients, we are better able to gauge the causal impact of report frequency. Figure 9 shows the results of a regression interacting the treatment effect (Treatment x After first mailing) with report frequency indicators. For kWh, monthly recipients reduce their usage by about 1.25% and quarterly recipients reduce their usage of about 1.05% However, for therms, both quarterly recipients reduce their usage about1.2%, with the quarterly households reducing slightly more than the monthly. In terms of the combined energy cost, the monthly group shows a slight improvement over the quarterly group, with the monthly group reducing 1.2% and quarterly group reducing 1.05%. On net, quarterly treatment effects are statistically indistinguishable from monthly effects. Given that quarterly reports are just as effective, and cost less to produce and mail, they appear to be the more efficient intervention.

The PSE data also allows us to investigate how the reductions in energy use change across the month, and observe how effects may vary based on proximity to the time the most recent report was sent out. Figures 10a and 10b report the results of a series of regressions (using full Table 3 controls) calculating the treatment effect in terms of kWh and therms for particular weeks before and after the experiment began. Figure 10a reports the week by week treatment effects on kWh and therms for recipients of monthly reports. The vertical lines denote the approximate delivery dates of the reports. All 6 mailings after the first mailing had treatment effects that were statistically lower than zero for both kWh and therms. Figure 10b analogously reports the weekly treatment effects for quarterly report recipients on kWh and therms. After the first mailing, 52% of the treatment effects observed on therms were statistically lower than zero for therms, and 77% of the treatment effects for kWh were statistically significant ($p. < .05$) reductions. Somewhat contrary to our expectations, there is no consistent or pronounced retrenchment for either monthly or quarterly recipients as the time from last report increases—although the reductions for the smaller quarterly recipients sample are less precisely measured. The lack of retrenchment suggests that the energy reductions may in large part be driven by durable behaviors, the effects of which would not wane with time; yet, as there is some retrenchment (such as in the electricity usage of quarterly recipients after the second report was received), some of the effect appears to be driven by non-durable behavior.

As in the SMUD experiment, we again see larger treatment effects for lower house value quintiles. Figure 11 shows that the lower three quintiles perform at or below the average reduction of 1.1%. Again, all quintiles saw a reduction, but in the two highest quintiles, the treatment reduction was not as pronounced.

Figure 12 reports the results of a regression (with the full set of controls) interacting the treatment effect with pretreatment energy usage deciles (based on household energy usage for the twelve months prior to the beginning of the experiment, adjusted for house size), with the reductions reported relative to control households in the same usage deciles. We see that in the PSE data the treatment effect is even more strongly correlated with the pretreatment energy usage. As in SMUD, we observe that the lower half of pretreatment energy users reduce usage less than the average reduction of 1.1% (in fact, for the 3 smallest deciles we estimate statistically significant *increases* in energy usage) while the higher half of pretreatment energy users reduce more than the average. Here the range of effects is wider than in the SMUD experiment, with the lowest pretreatment decile increasing usage by 3.4% (suggesting a more pronounced "boomerang" effect) and the highest pretreatment decile decreasing use by 6.0%. As mentioned earlier, these findings contradict Schultz, Nolan, Cialdini, Goldstein, and Griskevicius (2007), but do not give significant cause for concern as programs based on the treatment can be controlled so that the lowest energy users do not receive reports.

Finally, Table 4 assesses the potential economic and environmental impact if reports were sent to all households in PSE's customer base. Per household, monthly recipients save nearly $14 a year from kWh reduction and $11 a year from therms reduction for a total of nearly $25 saving a year. Quarterly recipients are only slightly behind, with total yearly savings of $22.28 ($11.19 from kWh and $11.09 from therms). With over 930,000 households receiving electric service and over 681,000 households receiving gas service from PSE, PSE customers would stand to save annually $23 million from monthly reports and $20.7 million from quarterly reports per year. In environmental terms this projected customer-base-wide savings from quarterly reports is the equivalent to saving the carbon emissions of 14.3 million gallons of gas. PSE households save $2.06 per mailing for the monthly reports and $5.57 per mailing for the quarterly reports. As we mentioned in the SMUD cost and impact analysis above, more research is needed into alternative delivery mechanisms for the reports, such as integration into the bill and electronic mail, in order to determine the most efficient and effective channels of communication. Selectively mailing reports only to households where we did not expect a "boomerang" effect would also increase the efficiency of the treatment.

IV. Conclusion

Both the PSE and SMUD experiments reveal that Positive Energy/oPower peer comparison reports cause significant reductions in home energy use, confirming the direction of the reductions found by Schultz, Wesley, Nolan, Cialdini, Goldstein, and Griskevicius (2007) in their earlier study in San Marcos. The PSE and SMUD experiments show that the effects of the report continue to be strong, up to seven and twelve months after the households begin to receive reports, respectively. The experiments analyzed here do contradict the findings of the San Marcos study to the extent we found a “boomerang” effect for both SMUD and PSE. The boomerang effects are not problematic, however, as reports can be targeted only at households where a boomerang effect is not expected. The experiments also teach us more about the most effective and efficient methods of designing the reporting system. In the SMUD experiment, out of four possible types of envelope size and report type combinations, the most effective was a graphical version of the report sent in a number 10 standard business size envelope. In the PSE experiment, perhaps surprisingly, sending the reports monthly did not have a significantly greater effect than sending them quarterly.

The experiments also reveal interesting dynamics about how different demographics were affected. In both experiments, households in the treatment group with lower house values saved more, on average, than households with higher house values. Also in both experiments, households with higher pre-treatment energy use saved more than households with lower pre-treatment energy use. The experiments also provide some evidence about the types of behavior that may be driving energy reductions, although more research is needed in this area. In both the SMUD and PSE studies, the significant reductions achieved in the period immediately after the first reports are sent out may suggest that changes may be behavioral rather than durable. Further supporting the idea that changes are behavioral is the fact that in the PSE experiment, the treatment group reduces its energy use more in a two day period roughly overlapping with the weekend, suggesting that reductions are caused by increased mindfulness, although the results are not conclusive. However, we also learn that the treatment effect does not wane as the time from the report increases, but instead is relatively smooth over the entire month or quarter, which may indicate that energy reductions are caused by more durable changes.

The Positive Energy/oPower experiments suggest that governmental entities should consider mandating or incentivizing peer comparison reporting. As we have shown in our simple calculations above, peer comparison reports can create significant net cost and carbon savings, benefiting both individual households and the environment. The efficiency of savings would be even more pronounced—and possible “boomerang effects” averted—if comparative information were only mandated for those who consume the most energy. Although some utilities, such as those that are publically owned (like SMUD), or private but regulated (like PSE), are beginning to provide such feedback, often utilities do not have adequate incentives to reduce energy consumption on their own. Government officials should also consider investing in scientifically designed studies that could increase knowledge in this area, such as determining the cost effectiveness of sending peer feedback inside the regular utility bill.

Finally, the Positive Energy/oPower experiments suggest that privately-delivered peer comparison feedback, such as direct mailings, might prove an effective tool in a range of other situations. There are endless ways public or private entities might employ such feedback to drive desired behavior. Schools might mail parents reports of how many absences or times late their children had compared to peers. Dentists might send mailings to their infrequent visitors indicating how often typical patients come in for cleanings. A gym might inform its lazier patrons of how often typical members work out. Government might even step in to require private entities conduct this type of reporting where it believes there are significant welfare gains. To take one example, the federal government might require that employers inform low-saving employees how much more their peers are saving in the company 401(k) plan. As these preliminary examples show, the area of peer comparison feedback is ripe for innovation and experimentation.

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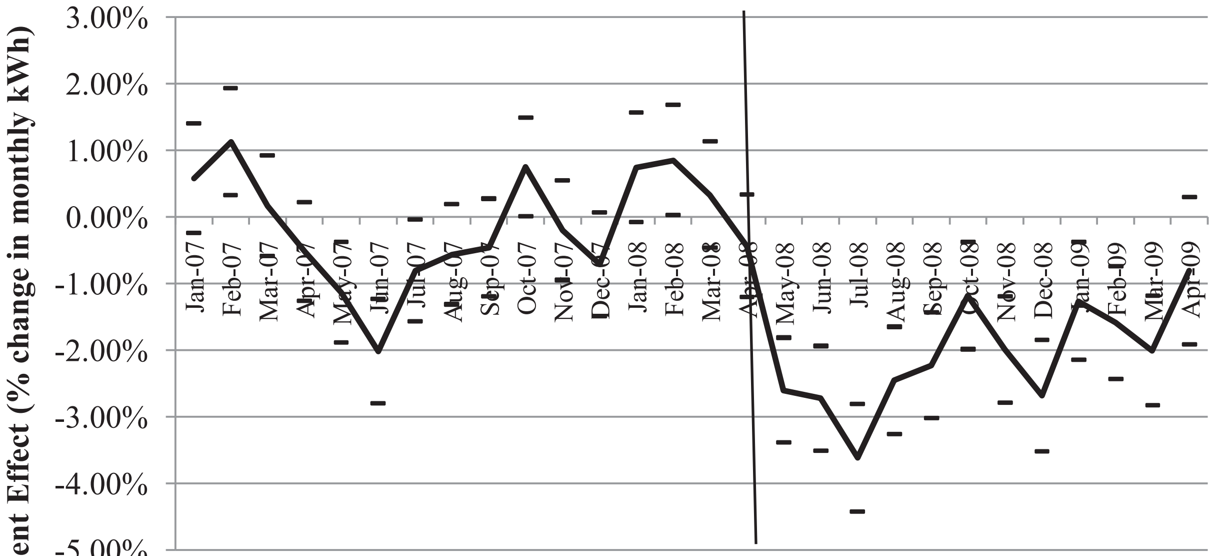
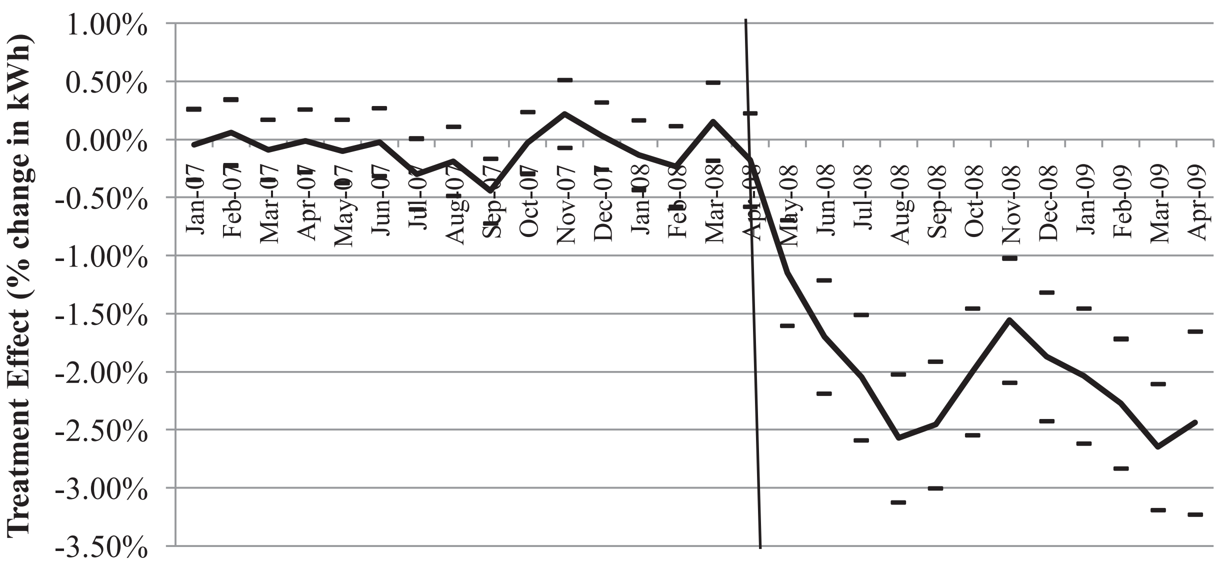
Figure 1: SMUD Treatment Effect
(% change in kWh - without controls)



*95% confidence intervals shown
**Vertical line indicates first mailing
***OLS regression on natural log of kWh/day clustered on household id with same controls as in Table 1

Figure 2: SMUD Treatment Effect
(% change in kWh- with controls)



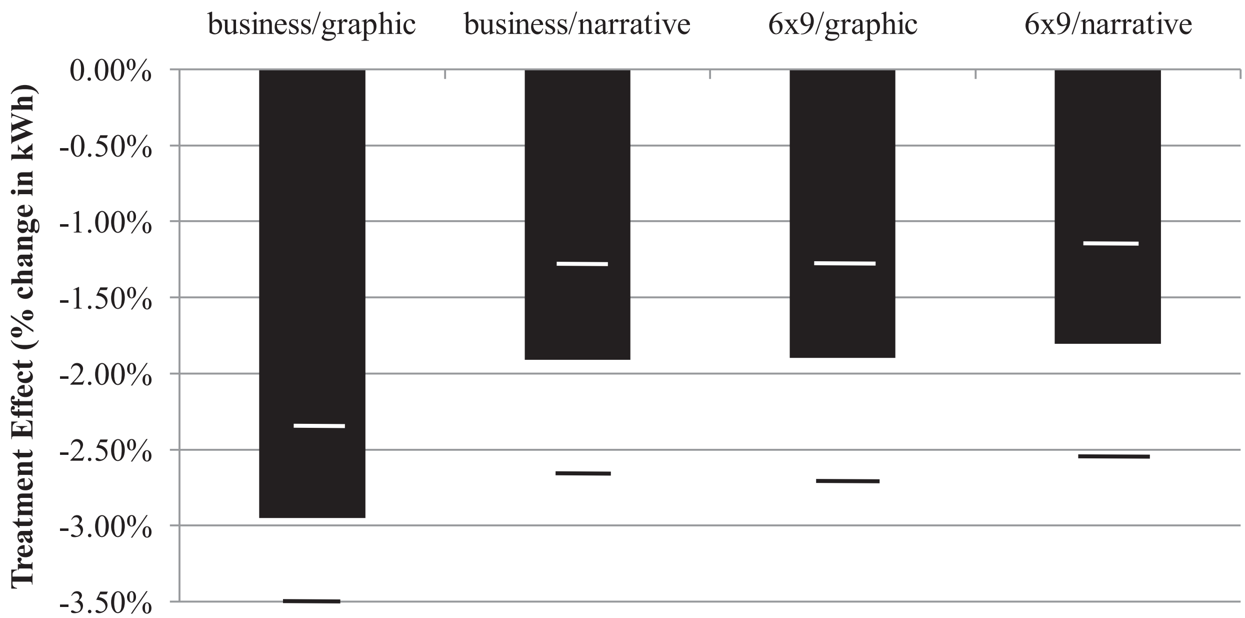
*95% confidence interval shown
**Vertical line indicates first mailing
***OLS regression on natural log of kWh/day clustered on household id with same controls as in Table 1

Table 1: SMUD OLS Regression of log household monthly average kWh/day, clustering on household id

	No controls n=2,262,815	With Controls n=1,585,490
Treatment household	-0.001	0.000
After first mailing (April '08)	-0.018 ***	0.078 ***
Treatment x After first mailing	-0.020 ***	-0.021 ***
Narrative template		0.001
6x9 envelope		0.001
Quarterly recipients		-0.117 ***
Cooling degree days		0.002 ***
Heating degree days		0.001 ***
House square foot		0.000 ***
House age		0.000 **
Pool		0.048 ***
Spa		-0.003
House value		0.000 ***
Gas heat		0.033 **
kWh/day usage in 2006		0.783 ***
Length of residence		-0.001 ***
Number in residence		0.008 ***
Head of household age effects	no	yes
Income quartile effects	no	yes
Affluence effects +	no	yes
Proprietary segment effects++	no	yes
Census tracts fixed effects	no	yes
Month Fixed Effects	no	yes
R-squared	0.001	0.706

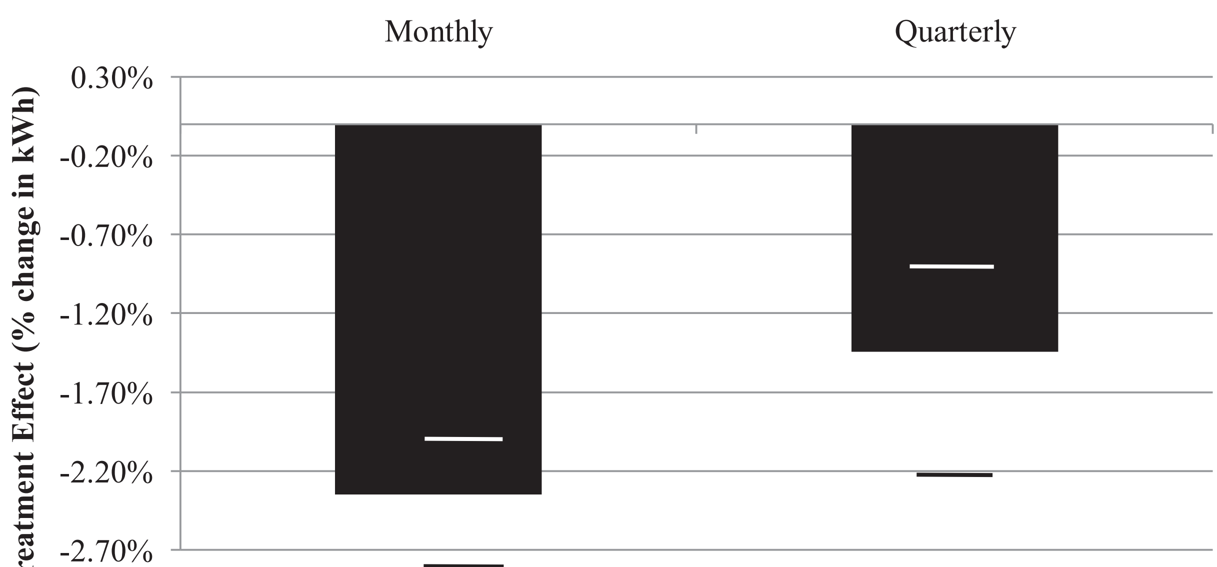
+Ten Affluence groups were created by Direct Group
++Proprietary segment groups created by Positive Energy based on house characteristics
*significance at the 90% level
**significance at the 95% level
***significance at the 99% level

Figure 3: SMUD Treatment Effect (% change in Kwh)
by templates/envelopes



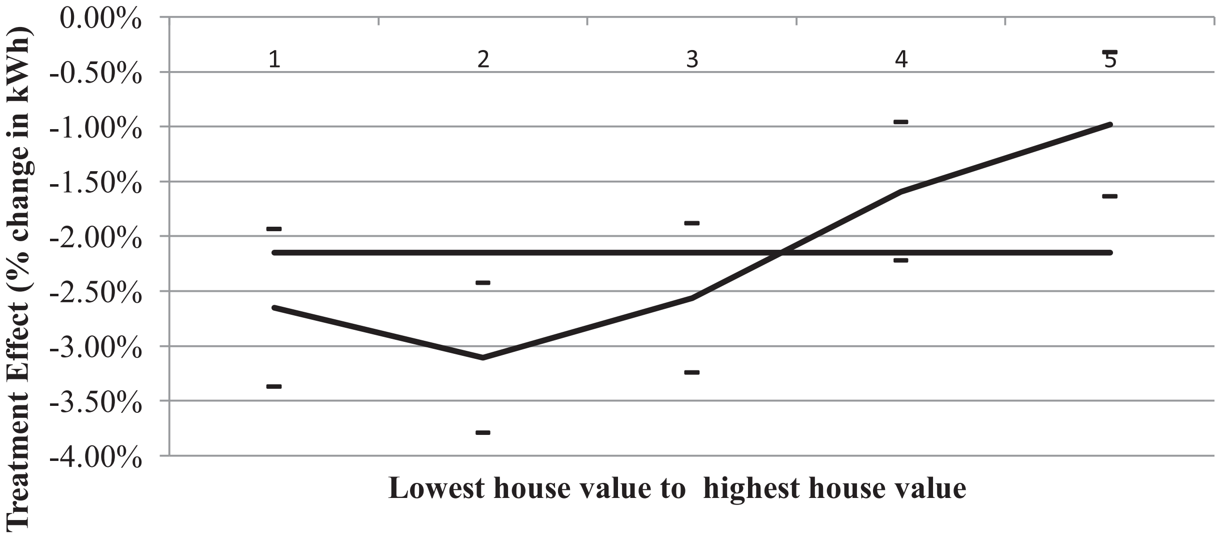
*95% Confidence interval shown
**OLS regression on natural log of kWh/day clustered on household id with same controls as in Table 1

Figure 4: SMUD Treatment Effect (% change in kWh)
by monthly vs quarterly reports



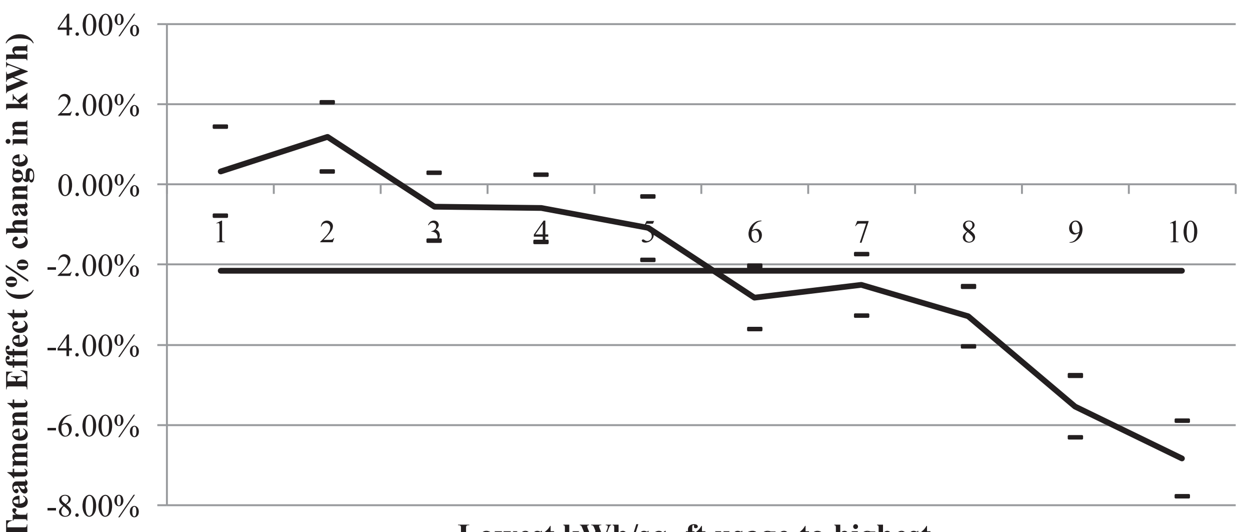
*95% Confidence interval shown
**OLS regression on natural log of kWh/day clustered on household id with same controls as in Table 1

Figure 5: SMUD Treatment Effect (% change in kWh) by house value quintile



*95% Confidence interval shown
**Horizontal line indicates average change in kWh
***OLS regression on natural log of kWh/day clustered on household id with same controls as in Table 1

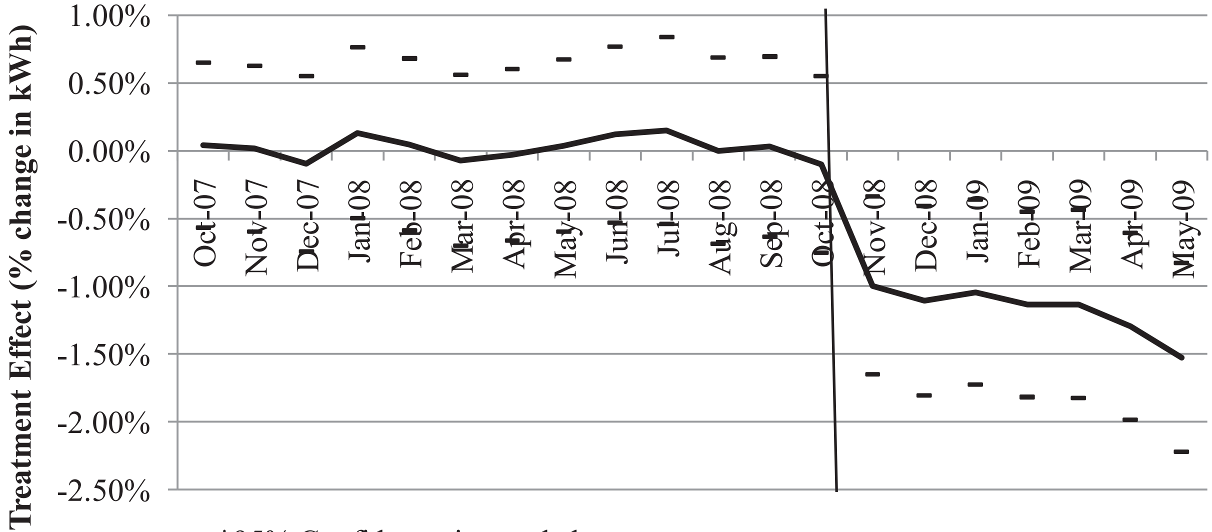
Figure 6: SMUD Treatment Effect (% change in kWh) by pretreatment kWh/sq. ft. usage



*95% Confidence interval shown
**Horizontal line indicates average change in kWh
***OLS regression on natural log of kWh/day clustered on household id with same controls as in Table 1

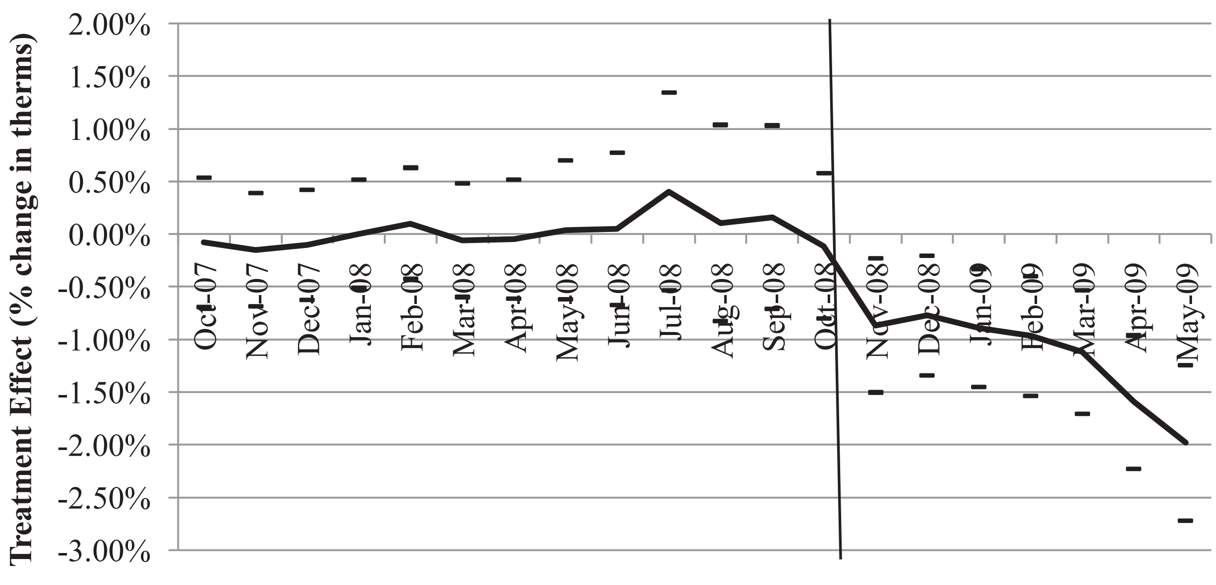
Table 2: SMUD Projected Cost Savings and Environmental Impact		
Per Household	**Monthly and Quarterly weighted effect**	
Reduction kWh/day		0.51
Reduction kWh in a year		187.20
Total savings in a year	$	25.74
Savings per mailing	$	2.78
For customer base of SMUD		
Annual kWh reduction		110,917,005
Annual reduction in metric tons CO2*		79,638
Annual reduction in gallons of gas**		9,039,547
Annual savings	$	15,250,601
*Based on 7.18 x 10-4 metric tons CO2 / kWh calculated by the EPA		
**Based on 8.81*10-3 metric tons CO2/gallon calculated by the EPA		

Figure 7a: PSE Treatment Effect
(% change in kWh-without controls)



*95% Confidence interval shown
**Vertical line indicates first mailing
***OLS regression on natural log of kWh/day clustered on household id with same controls as in Table 3

Figure7b: PSE Treatment Effect
(% change in therms -without controls)



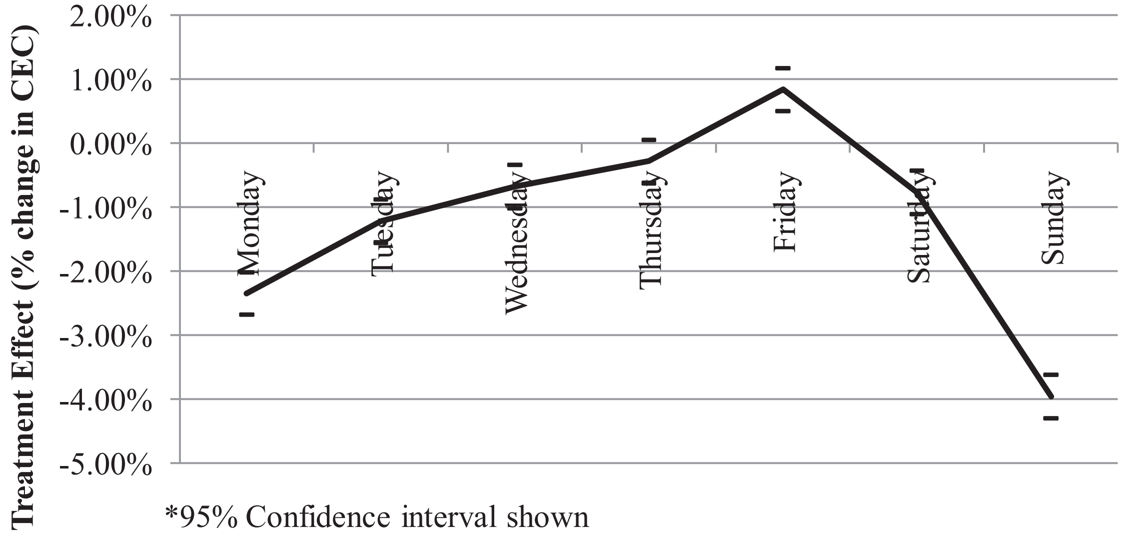
*95% Confidence interval shown
**Vertical line indicates first mailing
***OLS regression on natural log of kWh/day clustered on household id with same controls as in Table 3

Table 3: PSE OLS regression of natural log of kWh/day, therms/day, CEU/day clustering on household id

	kWh/day (without controls)	kWh/day (with controls)	therms/day (without controls)	therms/day (with controls) n=1410933	CEC/day (without controls)	CEC/day (with controls) n= 1420145
Treatment household	0.000	0.000	0.000	0.001	0.000	0.000
After first mailing (Oct '08)	0.042 ***	-0.292 ***	0.436 ***	-2.151 ***	0.218 ***	-1.005 ***
Treatment x After first mailing	-0.012 ***	-0.012 ***	-0.012 ***	-0.012 ***	-0.011 ***	-0.011 ***
House square foot		0.000 ***		0.000		0.000 ***
House age		0.000		-0.001 ***		0.000 ***
House value		0.000		0.000 **		0.000 ***
Quarterly recipient		-0.001		0.000		0.000
Therms usage in 2007		0.000 *		1.001 ***		0.410 ***
kWh usage in 2007		0.932		-0.001		0.465 ***
Cooling degree days		-0.001		-0.006 ***		-0.003 ***
Heating degree days		0.000		0.005 ***		0.002 ***
Proprietary segment effects +	no	yes	no	yes	no	yes
Month Fixed Effects	no	yes	no	yes	no	yes
R-Squared	0.001	0.717	0.065	0.849	0.043	0.810

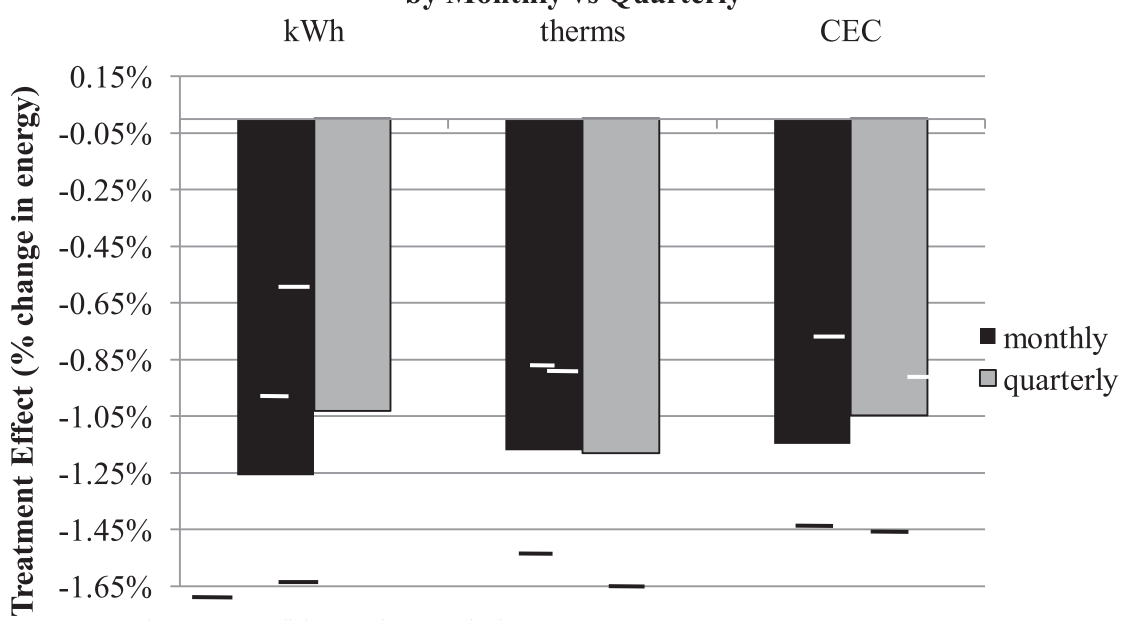
+Proprietary segment groups created by Positive Energy based on house characteristics
*significance at the 90% level
**significance at the 95% level
***significance at the 99% level

Figure 8: PSE Treatment Effect (% change in CEC)
Day of the Week



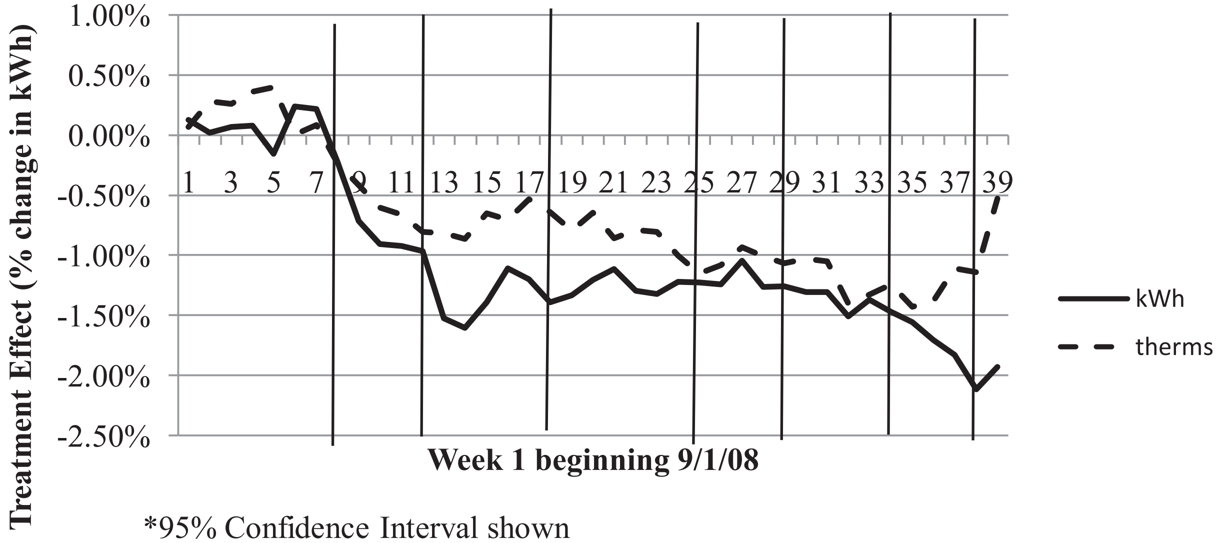
*95% Confidence interval shown
**OLS regression on natural log of CEC/day clustered on household id with same controls as in Table 3

Figure 9: PSE Treatment Effect
by Monthly vs Quarterly



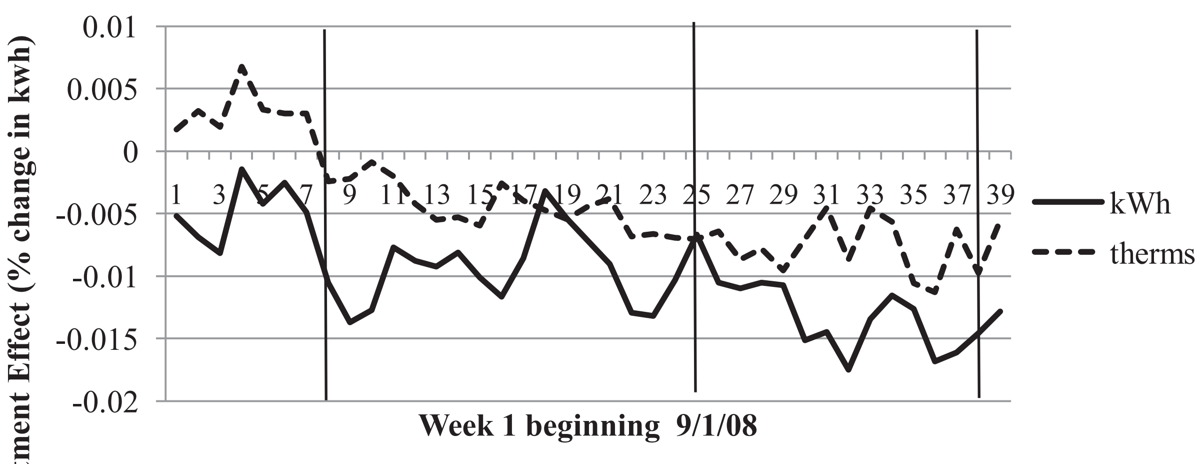
*95% Confidence interval shown
**OLS regression on natural log of energy use clustered on household id with same controls as in Table 3

Figure 10a: PSE Treatment Effect (% change in kWh and therms)- Monthly recipients



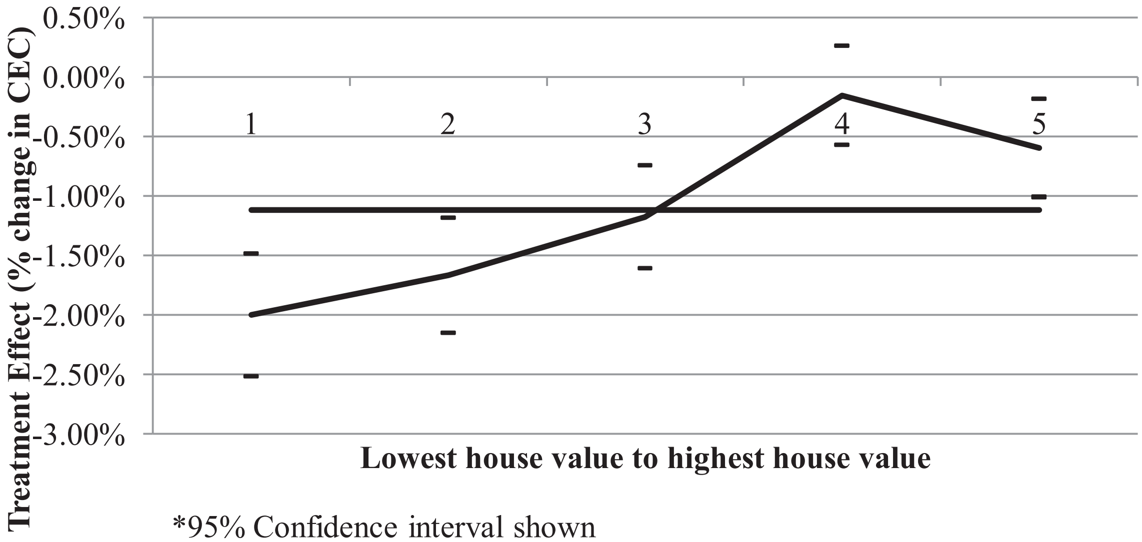
*95% Confidence Interval shown
**Vertical lines indicate mailings
***OLS regression on natural log CEC/day clustered on household id with same controls as in Table 3

Figure 10b: PSE Treatment Effect (% change in kwh and therms) - Quarterly recipients



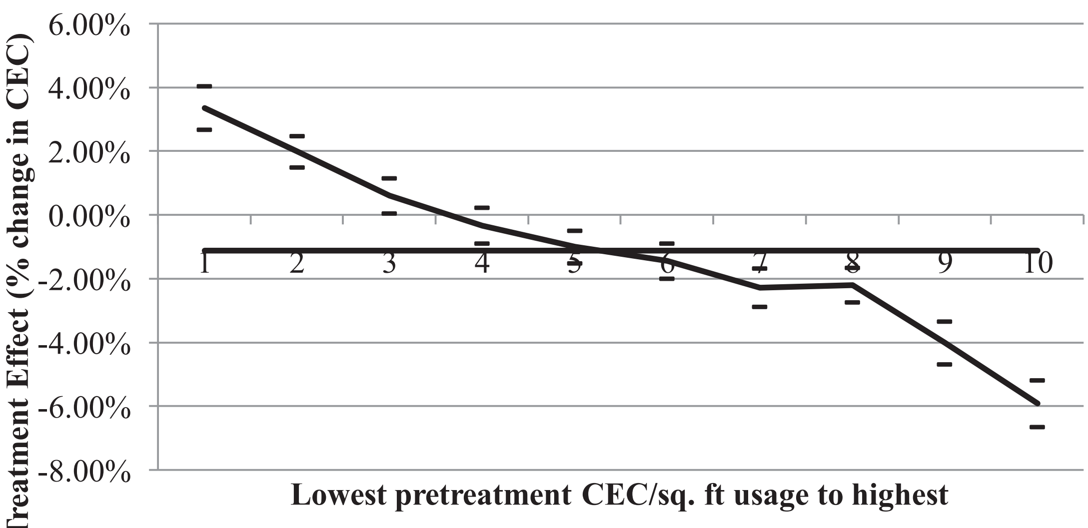
*95% Confidence Interval shown
**Vertical lines indicate mailings
***OLS regression on natural log CEC/day clustered on household id with same controls as in Table 3

Figure 11: PSE Treatment Effect (% change in CEC) by house value quintiles



*95% Confidence interval shown
**Horizontal line indicates average change in CEC
***OLS regression on natural log of CEC/day clustered on household id with same controls as in Table 3

Figure 12: PSE Treatment Effect (% change in CEC) by pretreatment CEC/sq. ft. deciles



*95% Confidence interval shown
**Horizontal line indicates average change in CEC
***OLS regression on natural log of CEC/day clustered on household id with same controls as in Table 3

Table 4: PSE Projected Cost Savings and Environmental Impact		
Per Household - kWh	**Monthly**	**Quarterly**
Reduction kWh/day	0.41	0.33
Total kWh reduction in a year	148.55	121.53
Total kWh savings in a year	$ 13.68	$ 11.19
Per Household - therms		
Reduction therms/day	0.028	0.028
Total therms reduction in a year	10.120	10.203
Total therms savings in a year	$ 11.00	$ 11.09
For customer base of PSE		
Annual Savings per household	$ 24.68	$ 22.28
Savings per mailing	$ 2.06	$ 5.57
Annual Savings for Puget Sound	$ 22,962,206	$ 20,730,469
Annual savings in metric tons of CO2*	3,169,489,576	115,943
Annual savings in gallons of gas**	391,295,009,340	14,313,900
*Based on 7.18 x 10-4 metric tons CO2 / kWh and 0.005 metric tons CO2/therm		
**Based on 8.81 x 10-3 metric tons CO2/gallon calculated by the EPA		

Not for Publication

A1: Mean comparison of all SMUD pre-treatment variables

Variable Name	Experiment n=34557	Control n=49570		Graphical n=41841	Narrative n=41856		#10 Envelope n=42276	6x9 envelope n=41851	
House square foot	1,737	1,753	***	1,742	1,732		1,731	1,743	*
House age	35.73	36.92		35.79	35.66		35.62	35.83	
Pool	0.21	0.22	***	0.21	0.21		0.20	0.21	*
Spa	0.04	0.04		0.04	0.04		0.04	0.04	
House value	$ 213,584	$215,189		$214,336	$212,833		$ 212,478	$ 214,690	
Gas heat	0.73	0.75		0.73	0.73		0.73	0.73	
Account closed	0.08	0.07		0.07	0.08		0.08	0.07	
Opt out	0.02	.		0.02	0.02		0.02	0.02	*
Quarterly recipient	0.29	0.29	*	0.29	0.29		0.29	0.29	
kWh usage in 2006	31.95	31.65	***	31.62	31.68		31.71	31.58	
Length of residence	14.03	14.21	**	14.11	13.94		13.99	14.06	
Number at residence	1.93	1.93		1.93	1.94		1.94	1.93	
Quartile 1 income group	0.11	0.11	**	0.11	0.11		0.11	0.11	
Quartile 2 income group	0.19	0.19		0.20	0.19	**	0.20	0.19	
Quartile 3 income group	0.16	0.16		0.16	0.16		0.16	0.17	
Quartile 4 income group	0.23	0.23		0.23	0.23		0.23	0.23	
Age- 24 years or less	0.00	0.00		0.00	0.00		0.00	0.00	
Age- 25-29	0.01	0.01		0.01	0.01		0.01	0.01	
Age- 30-34	0.03	0.03		0.03	0.03		0.03	0.03	
Age- 35-39	0.06	0.05		0.05	0.06		0.06	0.05	
Age- 40-44	0.07	0.07		0.07	0.07		0.07	0.07	
Age- 45-59	0.09	0.09		0.09	0.09		0.09	0.09	
Age- 50-54	0.10	0.10	*	0.10	0.10		0.10	0.10	
Age- 55-59	0.09	0.09	**	0.09	0.09		0.10	0.09	*
Age- 60-64	0.07	0.07		0.07	0.07		0.07	0.07	
Age- 65+ years	0.01	0.02		0.01	0.01		0.01	0.01	
Age- 65-69	0.05	0.05		0.05	0.05		0.05	0.05	
Age- 70-74	0.04	0.04		0.04	0.04		0.04	0.04	

A1 continued: Mean comparison of all SMUD pre-treatment variables

Variable Name	Experiment	Control n=49570		Graphical n=41841	Narrative n=41856	#10 Envelope n=42276	6x9 envelope n=41851
Age- 75+ years	0.07	0.07		0.07	0.07	0.07	0.08
kWh/day spent in…							
Jan-07	36.71	36.72		36.69	36.74	36.78	36.65
Feb-07	33.10	32.95		33.04	33.17	33.13	33.08
Mar-07	28.00	28.14		27.94	28.07	28.01	27.99
Apr-07	24.67	24.95	***	24.63	24.72	24.72	24.63
May-07	25.44	25.89		25.39	25.49	25.50	25.38
Jun-07	28.53	29.28		28.48	28.58	28.58	28.48
Jul-07	36.92	37.32	***	36.88	36.95	36.96	36.87
Aug-07	36.80	37.13	***	36.73	36.87	36.87	36.73
Sep-07	37.78	38.01	*	37.81	37.76	37.86	37.71
Oct-07	25.70	25.63		25.68	25.72	25.78	25.62
Nov-07	25.21	25.44	**	25.15	25.27	25.28	25.14
Dec-07	30.77	31.18	***	30.69	30.86	30.79	30.76
Jan-08	36.07	36.00		36.02	36.12	36.08	36.06
Feb-08	32.81	32.75		32.75	32.87	32.87	32.76
Mar-08	27.48	27.57		27.47	27.49	27.53	27.43

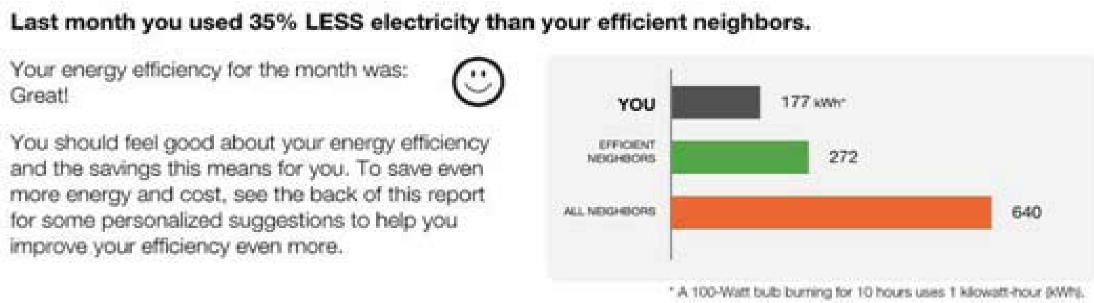
A1 continued: Mean comparison of all SMUD pre-treatment variables								
Variable Name	Experiment	Control n=49570		Graphical n=41841	Narrative n=41856		#10 Envelope n=42276	6x9 envelope n=41851	
Affluence1	0.01	0.01	**	0.01	0.01		0.01	0.01	
Affluence2	0.03	0.03	*	0.03	0.03		0.03	0.03	***
Affluence3	0.16	0.15		0.16	0.16		0.16	0.16	
Affluence4	0.10	0.10		0.10	0.10		0.10	0.10	
Affluence5	0.17	0.17		0.17	0.17		0.17	0.17	
Affluence6	0.10	0.08		0.10	0.10		0.10	0.10	
Affluence7	0.08	0.08		0.07	0.08		0.08	0.07	
Affluence8	0.04	0.08	**	0.04	0.04		0.04	0.04	
Affluence9	0.03	0.08		0.03	0.03		0.03	0.03	
Affluence10	0.00	0.08	***	0.00	0.00	**	0.00	0.00	
Greenergy	0.09	0.08		0.09	0.09		0.09	0.09	
Electric heat	0.27	0.08		0.27	0.26		0.27	0.27	

*significance at the 90% level
**significance at the 95% level
***significance at the 99% level

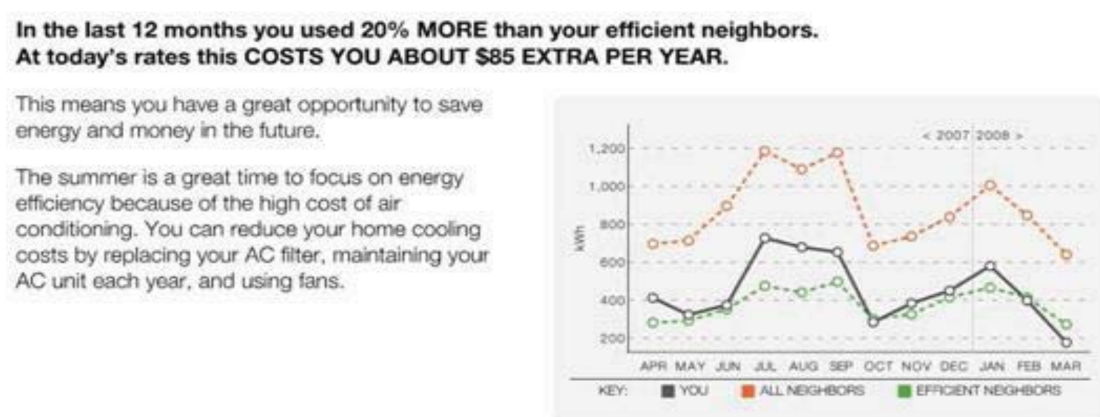
A2: Mean comparison of all PSE pre-treatment variables				
Variable Name	**Experiment n=34891**	**Control n=44121**	**Monthly n=24949**	**Quarterly n=9949**
House square foot	2138.56	2139.99	2139.316	2136.675
House age	29.98	29.98	30.05507	29.77646
House value	$ 345,046	$ 346,041	$ 345,874	$ 342,971
Account closed	0.02	0.02	0.0230069	0.0252287
Opt out	0.01 .		0.0096597	0.0023118 ***
Therms usage in 2007	2.50	2.50	2.503947	2.49931
kWh usage in 2007	30.31	30.26	30.22907	30.49656 *
Quarterly recipient	0.29	0.25 ***		
kwh/day use in…				
Oct-07	29.71	29.68	29.63603	29.89212
Nov-07	33.29	33.24	33.22576	33.46124
Dec-07	39.21	39.16	39.12722	39.42908
Jan-08	35.68	35.58	35.57679	35.92857 *
Feb-08	32.68	32.61	32.59502	32.8943
Mar-08	31.62	31.60	31.55034	31.80635
Apr-08	29.26	29.25	29.19247	29.41191
May-08	27.01	27.00	26.93957	27.19525
Jun-08	26.98	26.98	26.90792	27.168 *
Jul-08	26.16	26.16	26.09187	26.32582
Aug-08	27.14	27.20	27.06467	27.33903
Sep-08	26.60	26.62	26.546	26.71831
therms/day use in…				
Oct-07	2.45	2.45	2.454846	2.447256
Nov-07	3.69	3.69	3.690222	3.675695
Dec-07	4.63	4.63	4.639679	4.614194
Jan-08	5.07	5.07	5.080978	5.049723
Feb-08	3.95	3.94	3.955583	3.93895
Mar-08	3.84	3.84	3.849284	3.829371
Apr-08	3.07	3.07	3.073234	3.055617
May-08	1.61	1.61	1.609415	1.610046
Jun-08	1.37	1.37	1.368782	1.369664
Jul-08	0.66	0.66	0.6498722	0.6711754 ***
Aug-08	0.66	0.66	0.6489835	0.6704728 ***
Sep-08	0.96	0.96	0.961564	0.9733857

*significance at the 90% level
**significance at the 95% level
***significance at the 99% level

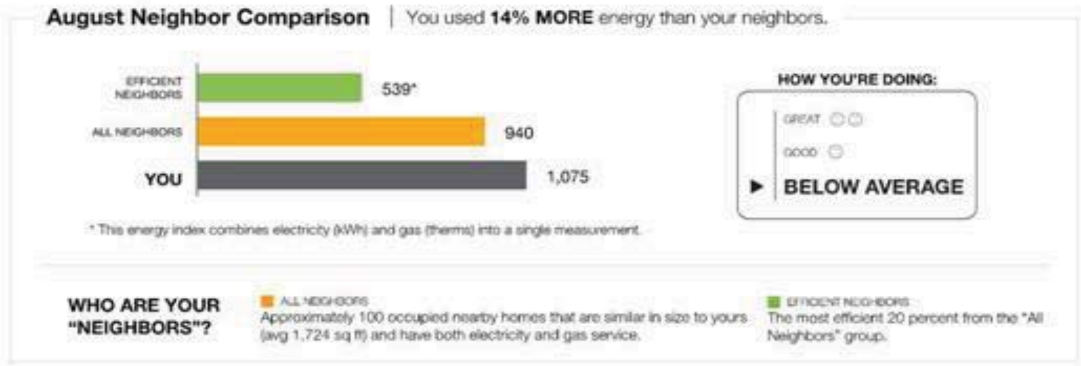
A3a: SMUD sample report, narrative template



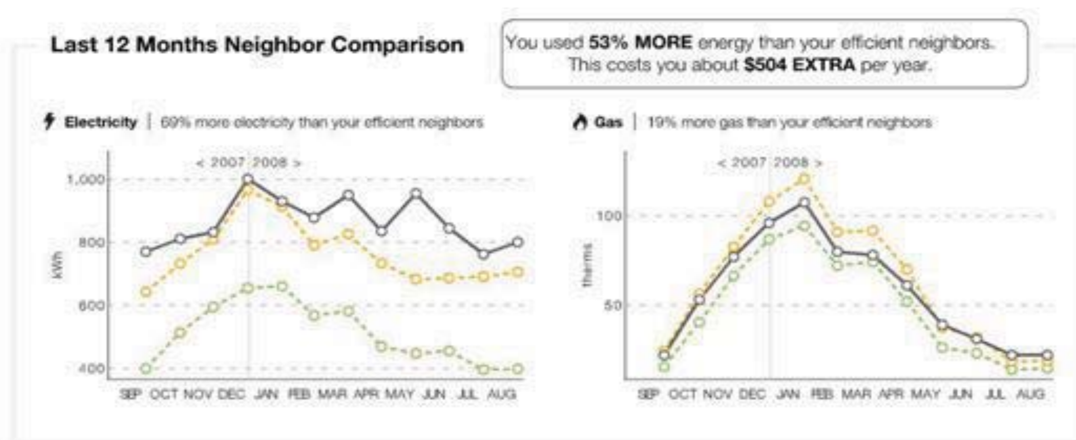
A3b: SMUD sample report, narrative template



A4a: PSE sample report



A4b: PSE sample report



IMPACT EVALUATION OF OPOWER SMUD PILOT STUDY

UPDATE – September 24, 2009

SUMMIT BLUE
CONSULTING, LLC

FINAL REPORT

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TABLE OF CONTENTS

1 EXECUTIVE SUMMARY

Information technologies designed to assist and encourage customers to use less energy are increasing in the industry. OPOWER offers an information program to help customers manage their energy use by providing reports comparing their energy use to the energy use of other similar households. These energy reports provide customers with normative comparisons of their current energy use compared to their neighbors and suggest actions that they can take to reduce their electric use. It is believed that there is a social driver at work in the presentation of energy use in this comparative fashion. If households learn they use more energy than their neighbors, it is assumed they will be motivated to reduce energy use and possibly do more than their neighbors.

OPOWER put this theory to the test with an aggressive experimental design across the Sacramento Municipal Utility District (SMUD). Census blocks were randomly assigned to treatment and control groups. Thirty-five thousand single-family residential customers in the treatment group received regular reports over the period of a year on how their energy use compared to their neighbors' energy use. Fifty thousand single-family customers in the control group did not receive any reports. The pilot began in April 2008. Billing data has been collected for all customers since the start of the program, including one year of billing data from before the test began, to support the impact evaluation of the program.

This report presents Summit Blue's independent third-party impact evaluation of the SMUD experimental design pilot conducted by OPOWER. The updated impact evaluation focuses on answering four basic research questions:

1. Does receiving the reports lead to energy savings?
2. Can the characteristics of large savers be identified?
3. What is the distribution of savings across customers?
4. What is the observed trend for energy savings in the second year of the pilot?

Does receiving the reports lead to energy savings?

Three different statistical methods were used to estimate savings from the program based on analysis of the first year of billing data. Table 1-1 shows that all three methods provided similar results, leading to the conclusion that the reports did indeed encourage customers to reduce their energy use. The estimate of annual savings from each of the three methods ranged from 2.1% to 2.2% showing strong robustness of results. The range around each of these estimates is tight, providing good reliability and precision.

The strength of these estimates rests on the clean design of the experiment and the very large sample sizes that were used. It is often difficult to accurately assess a program savings of 2% from billing analysis because of the wide range of variability in customer bills, but the large scale of this experiment allowed for accurate assessment of savings from this program. Given the consistent estimate of savings found across several methods and the tight range of precision around each estimate, it is clear that the OPOWER reports did encourage a reduction in energy use among customers who received them.

Table 1-1. Comparison of Savings Estimates from Three Statistical Methods

Method	*Average annual kWh savings*	*95% Confidence interval on avg. annual savings*	*Average annual percent savings*	*95% Confidence interval on avg. percent savings*
Method 1: Difference-in-Difference Statistic	257	-	2.20%	-
Method 2: Baseline OLS Linear Model	253.75	{216.81, 290.69)	2.24%	{1.91%, 2.56%}
Method 3: Baseline Differenced Linear Fixed Effects Model	240.88	{222.81, 258.95)	2.13%	{1.97%, 2.28%}

While annual savings were consistently estimated between 2.1% and 2.2%, this is an average of savings that actually varied by season across year one. Table 1-2 uses the difference in difference method to show that savings were the greatest during the summer at 2.6%, followed by a savings of 2.2% during the winter and 1.7% during the other shoulder months. Differences by season are reasonable and expected given that customers use electricity for different purposes during each season. Summer electric use and savings are the highest due to air-conditioning load. Winter use reflects additional lighting and some space heating. The shoulder months have the lowest overall use and savings.

Table 1-2. Savings by Season

Season	*Group*	*2007 KWH/Day*	*2008 KWH/Day*	*Difference KWH/Day*	*Percent Difference*
Summer: July, Aug, Sept Billing Months	Participants	37.53	37.10	-0.43	
	Control Group	37.83	38.37	+0.54	
				-0.97	-2.6%
Winter: Dec, Jan, Feb, Mar, Apr Billing Months	Participants	33.19	31.56	-1.63	
	Control Group	33.34	32.45	-0.89	
				-0.74	-2.2%
Shoulder Months: May, June, Oct, Nov	Participants	26.58	26.73	+0.15	
	Control Group	26.91	27.52	+0.61	
				-0.46	-1.7%

Participants with low electric use (less than 21.863 kWh/day) received reports quarterly while most participants received reports monthly

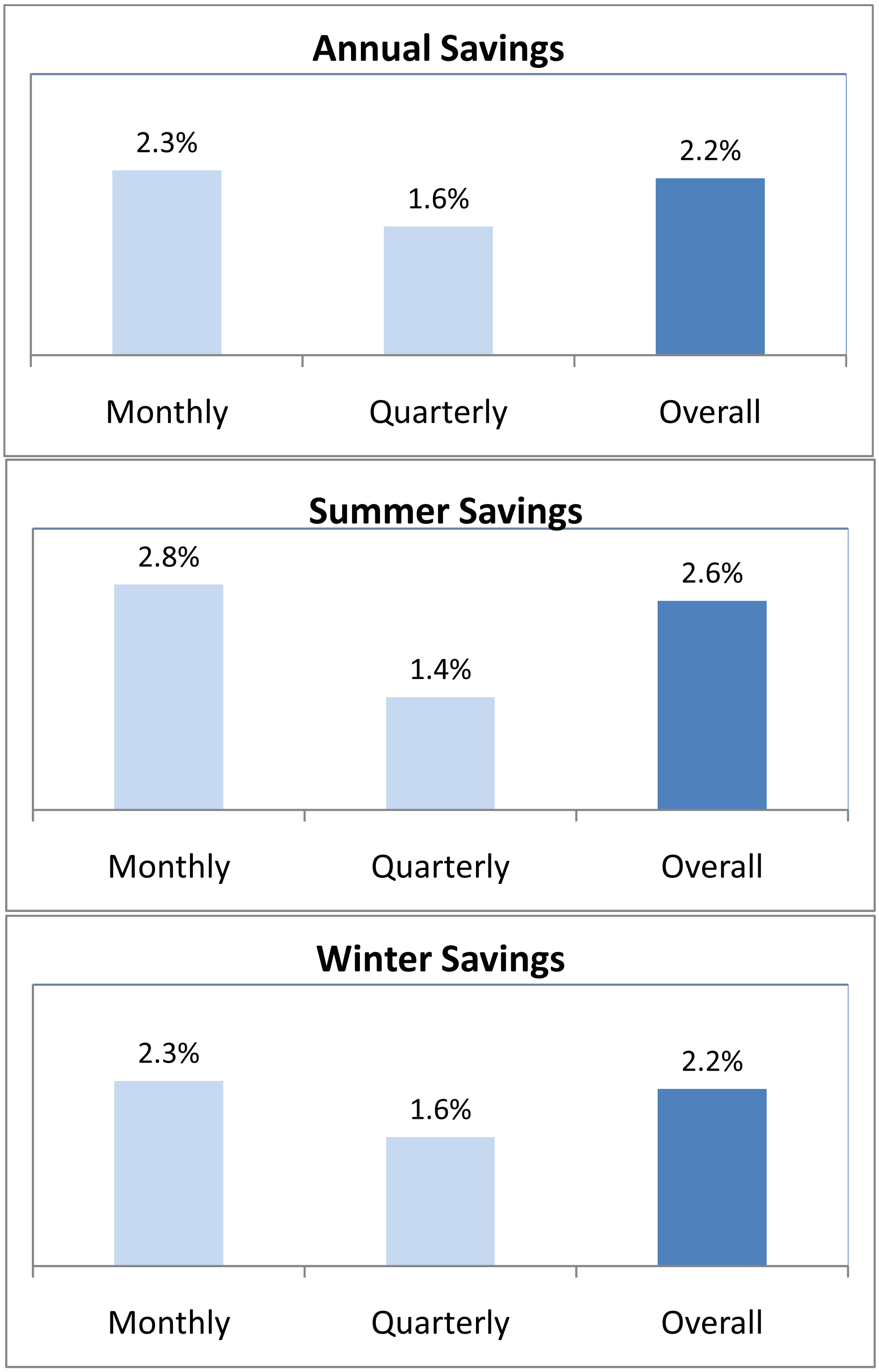
Table 1-3 shows that the high use customers receiving monthly reports achieved greater savings than low use customers receiving quarterly reports. However, both groups achieved savings in each season. Summer was the season showing the greatest savings for high use customers, while low use customers showed relatively consistent savings across all of the seasons.

Table 1-3. Comparison of Savings for Quarterly vs. Monthly Report Recipients

Method	*Summer Impact*	*Winter Impact*	*Shoulder Months Impact*	*Annual Impact*
Monthly Reports (High Use Customers)	-2.8%	-2.3%	-1.9%	-2.3%
Quarterly Reports (Low Use Customers)	-1.4%	-1.6%	-1.4%	-1.6%
Overall	-2.6%	-2.2%	-1.7%	-2.2%

These seasonal differences for the different report frequencies are illustrated in **Error! Reference source not found.**.1 on the next page.

Figure 1-1. Comparison of Savings for Monthly vs. Quarterly Report Recipients



Can the characteristics of large savers be identified?

Both methods 2 and 3 were used to test the contribution of different customer characteristics to savings.

Using method 2, it was found that the only housing characteristics that have a statistically significant effect on energy savings under the program are the presence of a pool and the value of the residence, though as a practical matter the effect of the latter is minor (a $10,000 increase in home value increases savings by 0.077 Kwh/day). The other housing characteristics examined in the analysis—*the presence of a spa, electric space heating, square footage and age of the home* —were not statistically significant at the .05 alpha level.

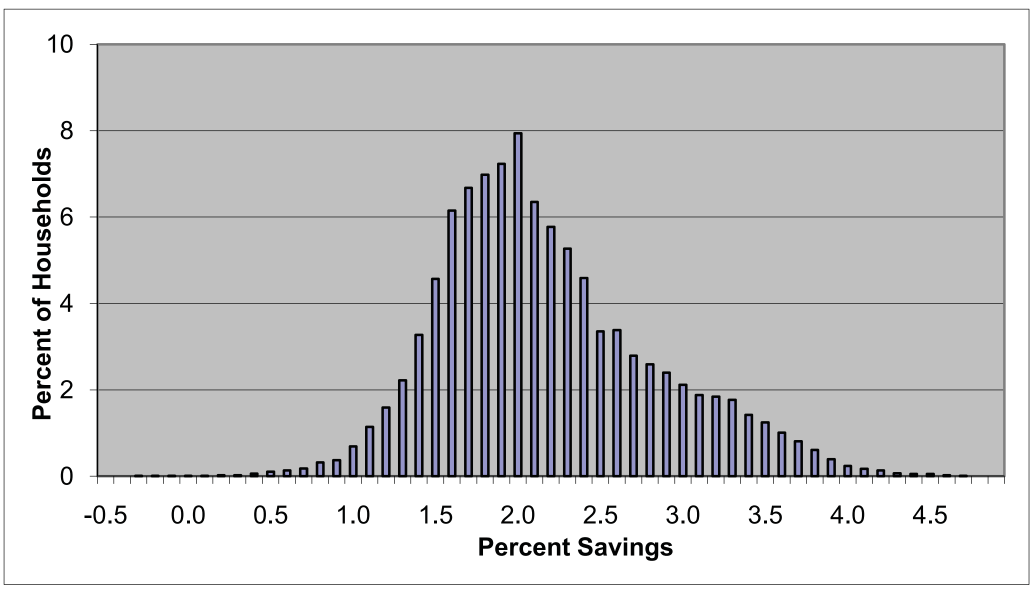
Using method 3, the only housing characteristic affecting energy savings is the presence of a pool.

The upshot of the analysis is that except for the presence/absence of a pool, it is difficult to forecast savings under the program based on housing characteristics. It must be remembered, however, that there is a strong savings response to cooling degree days which indicates that the presence of air conditioning contributes to the overall savings.

What is the distribution of savings across customers?

The method 2 linear regression model was used to predict the distribution of savings within the participant group. Figure 1-2 shows that savings were predicted for nearly all customers. As noted previously, the average savings is about 2.2%. Predicted percent savings for 50% of all households lie in the interval {1.6, 2.2}, predicted savings for 80% of all households lie in the interval {1.4, 2.9}, and predicted savings for 95% of all households lie in the interval {1.1, 3.5}.

Figure 1-2. Frequency distribution of predicted percent annual energy savings (2007 as base year) within the treatment group



This distribution curve shows that savings are predicted for virtually all individuals, rather than being possible for just a small subset of customers with particular characteristics. It is important to emphasize that this frequency distribution describes *expected* savings within the sample, *conditional* on observed housing characteristics such as square footage of the residence, the presence/absence of a pool, the assessed value of the residence, and so forth, based on the point estimates of the OLS regression of method 2. For a given set of housing characteristics, some households in the real world will generate greater savings and some less than indicated in this modeled distribution.

What is the observed trend for energy savings in the second year of the pilot?

Initial analysis based on four months of data from the second year of the pilot, May through August 2009, indicates that the energy savings are going up in the second year. Two of these months, May and June, are Shoulder Months while July and August are part of the Summer season. The difference of differences approach was used to estimate the savings over this entire four month period, and also to give a focused look at what happened over the two summer months.

Table 1-4. Second Year Savings based on Difference of Differences Method

Period	*Group*	*2007 kWh per Cust*	*2008 kWh per Cust*	*2009 kWh per Cust*	*2007-2008 Difference*	*Percent Savings*	*2007-2009 Difference*	*Percent Savings*
May, June, July, and August	Participants	3,921	3,909	3,769	-12		-152	
	Control Group	*3,979*	*4,054*	*3,935*	*75*		*-44*	
					-87	**-2.2%**	**-108**	**-2.8%**
July and August	Participants	2254	2260	2165	6		-89	
	Control Group	*2275*	*2345*	*2266*	*70*		*-9*	
					-64	**-2.8%**	**-80**	**-3.5%**

Table 1.4 shows that looking at both the four month period and the two month summer period, savings increased during the second year of the pilot compared to what was achieved in the first year. During the four month period of May, June, July and August, participants reduced their energy use by 2.2% in 2008 and then achieved even more savings in 2009, dropping their energy use by 2.8% from the base year period. This indicates that there is a cumulative effect to the program and as it continues over time the participants find additional ways to reduce their energy consumption, or, alternatively, additional participants start taking energy saving actions.

The cumulative increase in savings is even more pronounced when focusing only on the high use summer months of July and August. In these two months, participants reduced their energy use by 2.8% in 2008 and then managed to achieve a reduction of 3.5% in 2009. The ability to easily adjust their air-conditioning use, which is typically the largest electric use in homes during these months, is likely to be the cause of these higher summer month savings.

It is of interest to note that savings increased in the second year even while the months of May through August in 2009 were slightly cooler than the same months in 2008.

2 BACKGROUND AND OBJECTIVES

Information technologies designed to assist and encourage customers to use less energy are increasing in the industry. There are a wide variety of information technology options available for accomplishing this purpose. Some focus on hardware solutions that put devices into a customer's home to give them information on current energy use. These devices can be expensive.

OPOWER offers an alternative low cost information program to help customers manage their energy use by providing reports comparing their energy use to the energy use of other similar households. These energy reports provide customers with normative comparisons of their current energy use compared to their neighbors and suggest actions that they can take to reduce their electric use.

It is believed that there is a social driver at work in the presentation of energy use in this comparative fashion. If households learn they use more energy than their neighbors, it is assumed they will be motivated to reduce energy use and possibly do more than their neighbors.

OPOWER put this theory to the test with an aggressive experimental design across the Sacramento Municipal Utility District (SMUD). Census blocks were randomly assigned to treatment and control groups. Thirty-five thousand single-family residential customers in the treatment group received regular reports over the period of a year on how their energy use compared to their neighbors' energy use. Fifty thousand single-family customers in the control group did not receive any reports.

The pilot began in April 2008. Billing data has been collected for all customers since the start of the program, including one year of billing data from before the test began, to support the impact evaluation of the program. Summit Blue provided an initial impact evaluation of the program after one year of test data had been collected. The initial report was issued in May of 2009 and evaluated annual savings and savings by season for the first year. This report is an update of the original and provides results from additional billing data collected for May through August of 2009. Most of this update repeats the results of the first year analysis from the initial report, with updated savings estimates for the first four months of the second year of the pilot presented separately in Section 4.2.

Evaluation Objectives

The impact evaluation which is the focus of this report has both primary and secondary evaluation objectives related to the OPOWER customer reports that were tested in the SMUD pilot.

The primary objective is to answer the basic question:

> Does receiving the reports lead to energy savings?

Additional secondary objectives were also identified. These include:

1. What is the distribution of savings across customers?
2. Can the characteristics of large savers be identified?
3. What is the observed trend for energy savings in the second year of the pilot?

The remainder of this report will present the findings to these key evaluation questions.

3 ANALYSIS METHODS

A large set of data generated by a well-constructed experimental design was provided for estimation of impacts of the SMUD Pilot Study. We estimated program impacts using three distinct statistical approaches. Each approach is presented below. Results are presented in section 4.

3.1 Method 1: Difference-in-Difference Statistic

Assuming random assignment of a large number of treatment and control households, a simple difference-in-difference statistic provides a good estimate of the average annual household savings in energy use (measured in kwh) from the treatment.

Denote by $\overline{E}_{pg}$ the average annual rate of kwh use in period *p* (*p*=0 for the pre-treatment period, *p*=1 for the post-treatment period) by households in group *g* (*g*=0 for the treatment group, *g*=1 for control group). The difference-in-difference statistic is the difference between the control and treatment groups in the *change* in their annual rate of kwh use across the pre- and post-treatment periods. Formally,

$$\begin{aligned} \triangle E &= \left(\overline{E}_{11} - \overline{E}_{01}\right) - \left(\overline{E}_{10} - \overline{E}_{00}\right) \\ &= \triangle \overline{E}_1 - \triangle \overline{E}_0 \end{aligned} \quad . \tag{1}$$

Dividing the difference-in-difference statistic by the average energy use of the control group in the pre-treatment period gives the proportional reduction from treatment,

$$\text{Prop reduction} = \frac{\triangle E}{\overline{E}_{01}} \quad . \tag{2}$$

3.2 Method 2: Linear Regression (LR) Models

A second approach is to cast household energy use as a function of a variety of explanatory variables including: a) group membership (treatment vs. control); b) observation period (pre- versus post-treatment); c) relevant weather-related variables such as heating degree days; d) observable housing/household characteristics such as square footage of the residence and the number of household members; and e) an error term reflecting unobservable variables (or alternatively, variables that are not included in the available data set).

The simplest version convenient for exposition is a linear specification in which average daily use (*ADU*) of kilowatt-hours by household *k* in month t (where months are assigned consecutively throughout the study period), is a function of three variables: the binary variable $Treatment_k$, taking a value of 0 if household *k* is assigned to the control group, and 1 if assigned to the treatment group; the binary variable $Post_t$, taking a value of 0 if month *t* is in the pre-treatment period, and 1 if in the post-treatment period; and the interaction between these variables, $Treatment_k \cdot Post_t$. Formally,

$$ADU_{kt} = \alpha_0 + \alpha_1 Treatment_k + \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t + \varepsilon_{kt} \tag{3}$$

Three observations about this specification deserve comment. First, the treatment response is captured by the coefficient α_3. This term captures the *difference in the difference* in average daily kwh use between the treatment group and the control group across the pre- and post-treatment periods. In other words, whereas the coefficient α_2 captures the change in average daily kwh use across the pre- and post-treatment for the *control* group, the sum $\alpha_2 + \alpha_3$ captures this change for the treatment group.

Second, the coefficient α_1 captures the effect of assignment to the treatment group *before* the treatment is actually administered. Given assignment of households to the treatment group via random assignment of census blocks, the *a priori* expected value of α_1 is of course zero, though because the sample of census blocks in the analysis is finite it is not necessarily zero. In other words, including the variable $Treatment_k$ prevents the possibility of bias in the estimate of the treatment effect α_3 that would otherwise exist if households in the treatment group were systematically different than those in the control group.

Third, if the error term ε_{kt} is independent and identically distributed across observations, ordinary least squares (OLS) regression will generate unbiased and efficient estimates. As noted in section 3.3, if the error term includes unobservable housing/household characteristics, then errors are temporally correlated, and ordinary least squares (OLS) regression will generate inefficient parameter estimates. Nonetheless, OLS regression is a useful benchmark, will give good estimates if unobserved household-level effects are negligible, and the method discussed in section 3.3 addresses the case when they are not.

The model can be expanded to include three other types of variables. weather-related variables, housing/household characteristics, and treatment variables reflecting differences in the particular treatment of treatment households. For each of the weather variables and housing characteristics included in estimation, four terms are added: the variable itself; the variable interacted with $Treatment_k$ to capture differential effects due to treatment category; the variable interacted with $Post_t$ to capture differential effects of the variable due to exogenous shocks across the two study periods; and the variable interacted with the interaction $Treatment_k \cdot Post_t$ to capture the effect of the variable on the treatment response.

For each of the treatment variables included in estimation, three terms are added to the model: the variable interacted with $Treatment_k$, the variable interacted with $Post_t$, and the variable interacted with $Treatment_k \cdot Post_t$. This last interaction term captures the effect of the differential treatment on the treatment response.

Formally, defining $\mathbf{V}_k$ as a vector of treatment variables, $\boldsymbol{W}_t$ as a vector of weather characteristics in month t, and $\boldsymbol{Z}_k$ as a vector of housing/household characteristics for household k, we have the expanded linear model,

$$\begin{aligned} ADU_{kt} &= \alpha_0 + \alpha_1 Treatment_k + \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t \\ &+ \lambda_1 \mathbf{V}_k \cdot Treatment_k + \lambda_2 \mathbf{V}_k \cdot Post_t + \lambda_3 \mathbf{V}_k \cdot Treatment_k \cdot Post_t \\ &+ \beta_0 \mathbf{W}_t + \beta_1 \mathbf{W}_t \cdot Treatment_k + \beta_2 \mathbf{W}_t \cdot Post_t + \beta_3 \mathbf{W}_t \cdot Treatment_k \cdot Post_t \\ &+ \delta_0 \mathbf{Z}_k + \delta_1 \mathbf{Z}_k \cdot Treatment_k + \delta_2 \mathbf{Z}_k \cdot Post_t + \delta_3 \mathbf{Z}_k \cdot Treatment_k \cdot Post_t + \varepsilon_{kt} \end{aligned} \quad , \tag{4}$$

where the coefficients λ_i, β_i and δ_i are vector-valued of conformable dimension. In this model, the average daily treatment effect (ADTE) is the sum of all terms multiplying the interaction term $Treatment_k \cdot Post_t$:

$$ADTE_{kt} = \alpha_3 + \lambda_3 \mathbf{V}_k + \beta_3 \mathbf{W}_t + \delta_3 \mathbf{Z}_k \ . \tag{5}$$

3.3 Method 3: Differenced Linear Fixed Effects (DLFE) Model

The linear regression (LR) models of section 3.2 will generate biased estimates of treatment response *if* the household-specific error ε_{kt} is correlated with the treatment assignment variable $Treatment_k$. Given the careful experimental design of the study, this seems highly unlikely. However remote the possibility, it can be avoided by estimating a fixed effects model in which a household fixed effects parameter α_{0k} captures all household-specific effects on energy use that do not change over time, including those that are unobservable. With reference to section 3.2 above, and defining φ_k as the household-specific portion of the error, the fixed effects parameter is defined as:

$$\alpha_{0k} = \alpha_0 + \alpha_1 Treatment_k + \lambda_1 \mathbf{V}_k \cdot Treatment_k + \delta_0 \mathbf{Z}_k + \delta_1 \mathbf{Z}_k \cdot Treatment_k + \varphi_k \ , \qquad (6)$$

and the fixed effects model is the corresponding modification of (4):

$$\begin{aligned} ADU_{kt} &= \alpha_{0k} + \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t \\ &+ \lambda_2 \mathbf{V}_k \cdot Post_t + \lambda_3 \mathbf{V}_k \cdot Treatment_k \cdot Post_t \\ &+ \beta_0 \mathbf{W}_t + \beta_1 \mathbf{W}_t \cdot Treatment_k + \beta_2 \mathbf{W}_t \cdot Post_t + \beta_3 \mathbf{W}_t \cdot Treatment_k \cdot Post_t \\ &+ \delta_2 \mathbf{Z}_k \cdot Post_t + \delta_3 \mathbf{Z}_k \cdot Treatment_k \cdot Post_t + \varepsilon_{kt} \end{aligned} \qquad (7)$$

In the fixed effect model, estimation of the set of parameters $\{\alpha_0, \alpha_1, \delta_0, \delta_1\}$ in the LR model (4) is replaced by estimation of the fixed effects parameter α_{0k} for *each* household in the sample; in the current study of approximately 85,000 households, this is not a feasible exercise. We instead take advantage of the favorable properties of the fixed effects model—in particular the elimination of the aforementioned potential bias—while avoiding the estimation of the fixed effects parameters, as follows. First, the average of monthly *ADU* is modeled for each household using (7), by taking the average over all variables (this includes the average of variables that are interactions). Using (7) to average across all such monthly observations for a household gives (where "bars" on variables indicate means):

$$\begin{aligned} \overline{ADU}_k &= \alpha_{0k} + \alpha_2 \overline{Post}_t + \alpha_3 \left(\overline{Treatment_k \cdot Post_t}\right) \\ &+ \lambda_2 \left(\overline{\mathbf{V}_k \cdot Post_t}\right) + \lambda_3 \left(\overline{\mathbf{V}_k \cdot Treatment_k \cdot Post_t}\right) \\ &+ \beta_0 \overline{\mathbf{W}}_t + \beta_1 \left(\overline{\mathbf{W}_t \cdot Treatment_k}\right) + \beta_2 \left(\overline{\mathbf{W}_t \cdot Post_t}\right) + \beta_3 \left(\overline{\mathbf{W}_t \cdot Treatment_k \cdot Post_t}\right) \\ &+ \delta_2 \left(\overline{\mathbf{Z}_k \cdot Post_t}\right) + \delta_3 \left(\overline{\mathbf{Z}_k \cdot Treatment_k \cdot Post_t}\right) + \overline{\varepsilon}_{kt} \end{aligned} \ . \qquad (8)$$

Equation (8) is then subtracted from (7) for each household. This generates deviations in monthly household ADU from the household's average monthly ADU. Defining deviations by the symbol "$\vartriangle$" (so, for instance, the deviation in the dependent variable is $\vartriangle ADU_{kt} = ADU_{kt} - \overline{ADU}_k$), we have,

$$\begin{aligned}\vartriangle ADU_k &= \alpha_2 \vartriangle Post_t + \alpha_3 \vartriangle\left(Treatment_k \cdot Post_t\right)\\ &+\lambda_2 \vartriangle\left(\mathbf{V}_k \cdot Post_t\right) + \lambda_3 \vartriangle\left(\mathbf{V}_k \cdot Treatment_k \cdot Post_t\right)\\ &+\beta_0 \vartriangle \mathbf{W}_t + \beta_1 \vartriangle\left(\mathbf{W}_t \cdot Treatment_k\right) + \beta_2 \vartriangle\left(\mathbf{W}_t \cdot Post_t\right) + \beta_3 \vartriangle\left(\mathbf{W}_t \cdot Treatment_k \cdot Post_t\right)\\ &+\delta_2 \vartriangle\left(\mathbf{Z}_k \cdot Post_t\right) + \delta_3 \vartriangle\left(\mathbf{Z}_k \cdot Treatment_k \cdot Post_t\right) + \vartriangle \varepsilon_{kt}\end{aligned} \quad (9)$$

Note that because the fixed effect α_{0k} is the same in every observation period, $\bar{\alpha}_{0k} = \alpha_{0k}$, it is eliminated from (9). Moreover, if ε_{kt} in (7) is an independent and identically distributed normal random variable, then so too is $\vartriangle\varepsilon_{kt}$, and unbiased parameter estimates are obtained via OLS regression. Finally, the equation generating the estimate of the average daily treatment effect is the same as in the LR model, equation (5).

3.4 Summary of Methods: Relative Strengths and Weaknesses

The difference-in-difference statistic (method 1) has the advantage of simplicity. However, if the assignment of households to the treatment and control groups is not random, or the sample is small, it may deviate substantially from the true treatment effect. Moreover, it provides no information about the effect of household characteristics and treatment variables on program efficacy.

The LR models of method 2 allow examination of the effect of housing/household characteristics on the treatment effect. The main potential disadvantage of these models is that if unobservable housing/household characteristics affecting the treatment response are correlated with assignment to the treatment group—highly unlikely given the careful experimental design of the study—the estimated effect of the average treatment response will be biased. Moreover, correlation of household-level unobservables over time and/or across households will bias the estimates of standard errors and therefore invalidate statistical inference (more on this in the concluding paragraph of this section below).

The DLFE models of method 3 forego the opportunity to estimate the effect of housing/household characteristics on average daily use of kwh in exchange for assuring no bias in estimates of the average treatment response due to correlation between housing/household characteristics and household assignment across the treatment and control groups. All housing/household characteristics that do not change over time—observable and unobservable characteristics alike—are embedded in the fixed effect, which in turn is eliminated from estimation by differencing. It is important to emphasize, though, that estimating the effect of housing characteristics and treatment variables on treatment response *is* possible, because the variables used to measure this effect—interactions involving the variable $Post_t$—do change over time.

We present the results of all three methods to demonstrate that the estimate of overall savings is robust to the modeling approach. But on theoretical grounds we strongly favor the third method—the DLFE model—because of the role that the household-level fixed effect parameters play in eliminating correlation among errors. This correlation may have severe consequences for statistical inference and may arise for several reasons. The most obvious is that certain unobservable household characteristics likely persist over time. A second is that certain unobservables may be common to households within a neighborhood, causing spatially-correlated errors across households within a neighborhood. Finally, despite the randomization by census block of the assignment of households to the treatment and control groups, there remains the possibility that households within the control group, or within the treatment group, share certain unobservable characteristics.

In the LR model we account for this last source of correlation by including the treatment variable *Treatment*$_k$, which effectively removes the correlation from the error term by capturing treatment-specific unobservables in the coefficient α_1. In the absence of census-block dummy variables in the model, it is possible that α_1 is also capturing spatial correlations across households, because of the block randomization of the experiment. The DLFE model addresses all three sources of correlation by sweeping them into the household-level fixed effects parameter and then eliminating this parameter from estimation by differencing the data. In other words, this approach accounts for household-specific unobservables broadly defined, including neighborhood-level unobservables (a characteristic of the household is its neighborhood) and unobservables possibly arising from the particular grouping of households into treatment vs. control (a characteristic of the household is its assignment to treatment vs. control).

4 FINDINGS

The calculation of the difference-in-difference statistic from (1) is straightforward, but the calculation of energy savings from the LR model (method 2) and the DLFE model (method 3) depends on the particular specification of the models. In the next section we provide the average annual savings generated by the difference-in-difference statistic and the *baseline* LR and DLFE models. In section 4.2, we discuss the baseline LR and DLFE models in more detail, and in section 4.4 we expand the LR model to examine the effect of household characteristics on the treatment response. In section 4.5, we examine the distribution of savings in the population, including the difference in savings between households contacted monthly and those contacted quarterly.

4.1 Estimates of Average Annual Savings

As discussed in the previous section, three different methods were used to estimate average annual savings from the program. Results from each method will now be presented.

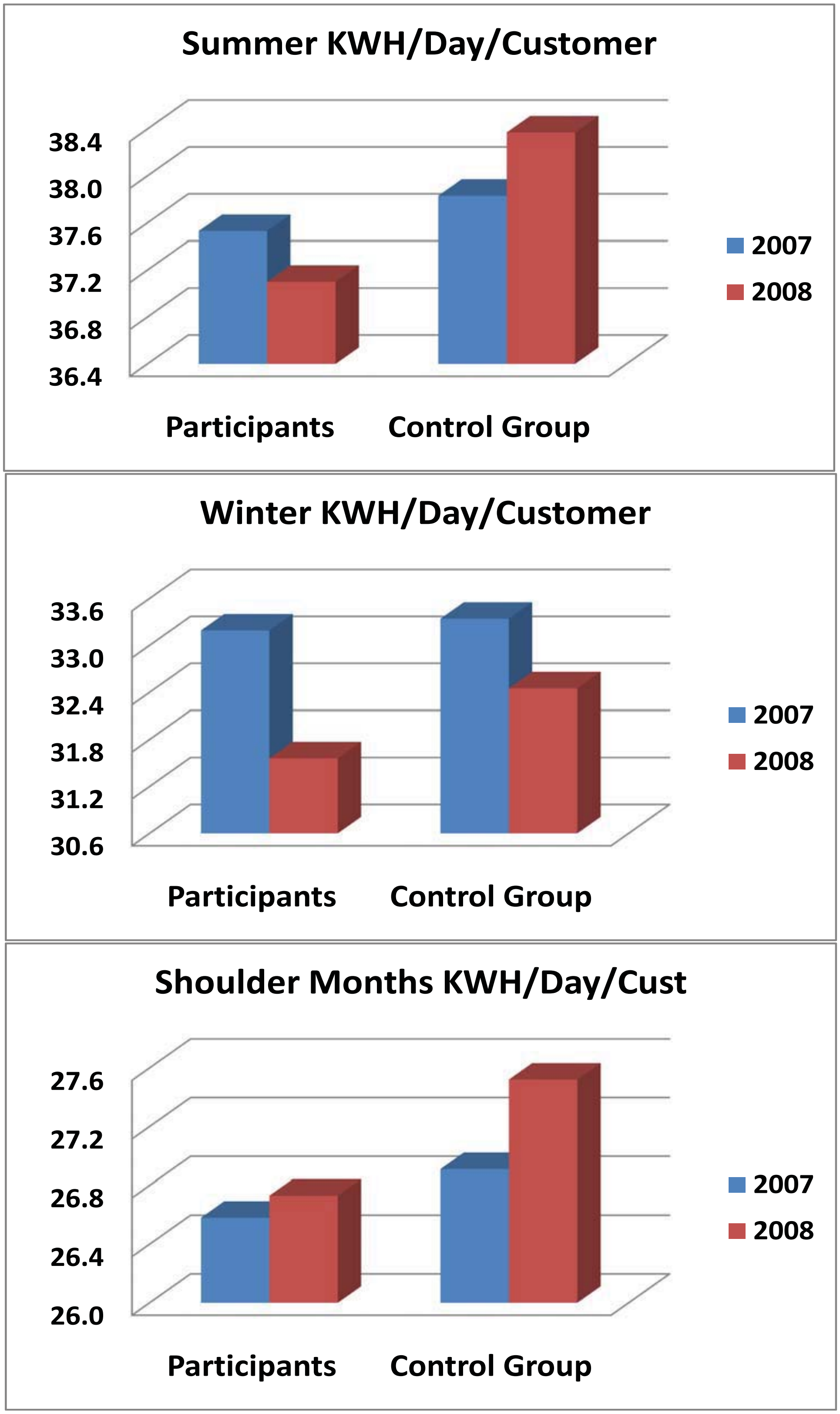
Table 4-1 summarizes the estimation of savings by season using method 1, the difference in differences approach, with the first full year of billing data . It shows that savings were the greatest during the summer at 2.6%, followed by a savings of 2.2% during the winter and 1.7% during the other shoulder months. Differences by season are reasonable and expected given that customers use electricity for different purposes during each season. Summer electric use, and savings, are the highest due to air-conditioning load. Winter use reflects additional lighting and some space heating. The shoulder months have the lowest overall use and savings.

Table 4-1. Savings by Season from Difference in Differences Method

Season	*Group*	*2007 KWH/Day*	*2008 KWH/Day*	*Difference KWH/Day*	*Percent Difference*
Summer: July, Aug, Sept Billing Months	Participants	37.53	37.10	-0.43	
	Control Group	37.83	38.37	+0.54	
				-0.97	-2.6%
Winter: Dec, Jan, Feb, Mar, Apr Billing Months	Participants	33.19	31.56	-1.63	
	Control Group	33.34	32.45	-0.89	
				-0.74	-2.2%
Shoulder Months: May, June, Oct, Nov	Participants	26.58	26.73	+0.15	
	Control Group	26.91	27.52	+0.61	
				-0.46	-1.7%

The consistent savings behavior of the participants across all of the seasons can be clearly seen in Figure 4-1. This is most dramatic during the summer when participants reduce their use while control group use increases.

Figure 4-1. Savings by Season from Difference in Differences Method



The observed savings per day by season can be used to estimate the annual savings from the program based on the first full year of data. Table 4-2 shows that the estimated annual savings is 257 kWh per customer which represents a 2.2% reduction in use for participants.

Table 4-2. Annual Savings from Difference in Difference Method

Method	*KWH per Day per Customer Difference*	*Days per Year*	*Annual KWH Savings per Customer*	*Percent Savings*
Summer	-0.97	92	-89	
Winter	-0.74	151	-112	
Shoulder Months	-0.46	122	-56	
Annual			-257	-2.2%

Estimated savings from methods 2 and 3 are based on a baseline model specification in which terms concerning heating and cooling degree days are added to the simplest model (3). In particular, the baseline LR model is,

$$\begin{aligned} ADU_{kt} &= \alpha_0 + \alpha_1 Treatment_k + \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t \\ &+ \beta_{H0} HDDd_t + \beta_{H1} HDDd_t \cdot Treatment_k + \beta_{H2} HDDd_t \cdot Post_t + \beta_{H3} HDDd_t \cdot Treatment_k \cdot Post_t \\ &+ \beta_{C0} CDDd_t + \beta_{C1} CDDd_t \cdot Treatment_k + \beta_{C2} CDDd_t \cdot Post_t + \beta_{C3} CDDd_t \cdot Treatment_k \cdot Post_t + \varepsilon_{kt} \end{aligned} \quad ,(10)$$

where $HDDd_t$ is heating degree days per day in month t, and $CDDd_t$ is cooling degree days per day in month t. Similarly, the baseline DLFE model is,

$$\begin{aligned} ADU_{kt} &= \alpha_2 Post_t + \alpha_3 Treatment_k \cdot Post_t \\ &+ \beta_{H0} \Delta HDDd_t + \beta_{H1} \Delta(HDDd_t \cdot Treatment_k) + \beta_{H2} \Delta(HDDd_t \cdot Post_t) + \beta_{H3} \Delta(HDDd_t \cdot Treatment_k \cdot Post_t) \\ &+ \beta_{C0} \Delta CDDd_t + \beta_{C1} \Delta(CDDd_t \cdot Treatment_k) + \beta_{C2} \Delta(CDDd_t \cdot Post_t) + \beta_{C3} \Delta(CDDd_t \cdot Treatment_k \cdot Post_t) + \varepsilon_{kt} \end{aligned} \quad . (11)$$

From (5), for both models the effect of treatment on average daily Kwh use—the average daily treatment effect (ADTE)— is,

$$ADTE_t = \alpha_3 + \beta_{H3} HDDd_t + \beta_{C3} CDDd_t \ . \quad (12)$$

Expanding (12) by using 2007 values of $HDDd_t$ and $CDDd_t$ generates the equation used in the calculation of annual savings due to the treatment effect (*AnnTE*) reported in Table 4-3:

$$AnnTE = \alpha_3 \cdot 365 + \beta_{H3} \cdot 2622 + \beta_{C3} \cdot 853 \quad (13)$$

Table 4-3 compares the estimated annual savings from each of the three methods. Two results deserve comment. First, all three methods give approximately the same result of an annual savings of about 2.1-2.2%. We found this result to hold across a wide variety of model specifications. Second, these estimates are very reliable, having a range of 1.9 to 2.6% at the 95% confidence level. The confidence intervals for methods 2 and 3 were calculated using the delta method (Greene 2002). They reflect the degree of precision in model parameter estimates, and are based on energy use in the sample in 2007 (the pre-treatment period), and thus on heating and cooling degree days in 2007. Along with the mean savings, these intervals would expand or contract somewhat depending on annual weather.

Table 4-3. Summary of Average Annual KWH Savings

Method	*Average annual kWh savings*	*95% Confidence interval on avg. annual savings*	*Average annual percent savings*	*95% Confidence interval on avg. percent savings*
Method 1: Difference-in-Difference Statistic:	257	-	2.20%	-
Method 2: Baseline OLS Linear Model	253.75	{216.81, 290.69)	2.24%	{1.91%, 2.56%}
Method 3: Baseline Differenced Linear Fixed Effects Model	240.88	{222.81, 258.95)	2.13%	{1.97%, 2.28%}

4.2 New Results with Additional Data

This section presents updated savings results for the first four months of the second year of the pilot, May through August 2009. Two of these months, May and June, are Shoulder Months while July and August are part of the Summer season. This update uses the difference of differences approach to estimate the savings seen in the additional data. First we will look at total savings over the new four months, and then we will give a focused look at what happened over the two summer months.

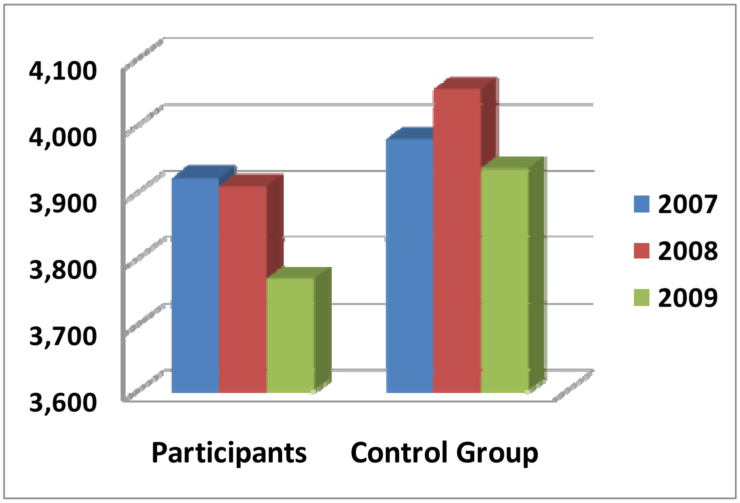
Table 4-4. Second Year Savings based on Difference of Differences Method

Period	*Group*	*2007 kWh per Cust*	*2008 kWh per Cust*	*2009 kWh per Cust*	*2007-2008 Difference*	*Percent Savings*	*2007-2009 Difference*	*Percent Savings*
May, June, July, and August	Participants	3,921	3,909	3,769	-12		-152	
	Control Group	*3,979*	*4,054*	*3,935*	*75*		*-44*	
					-87	**-2.2%**	**-108**	**-2.8%**
July and August	Participants	2254	2260	2165	6		-89	
	Control Group	*2275*	*2345*	*2266*	*70*		*-9*	
					-64	**-2.8%**	**-80**	**-3.5%**

Table 4.4 shows that looking at both the four month period and the two month summer period, savings increased during the second year of the pilot compared to what was achieved in the first year. During the four month period of May, June, July and August, participants reduced their energy use by 2.2% in 2008

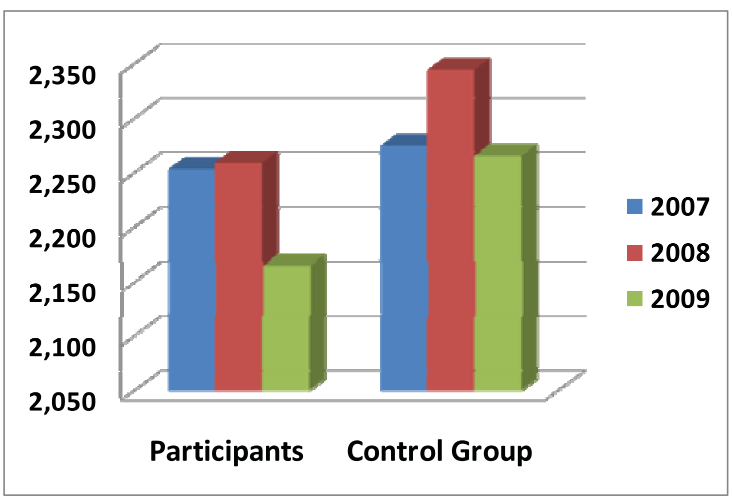
and then achieved even more savings in 2009, dropping their energy use by 2.8% compared to the base year period. This indicates that there is a cumulative effect to the program and as it continues over time the participants find additional ways to reduce their energy consumption, or, alternatively, additional participants start taking energy saving actions. Figure 4.2 illustrates how average kWh per customer changed for the participants and the control group during these four months over the study timeframe.

Figure 4-2. Average kWh per Customer for May, June, July and August



The cumulative increase in savings is even more pronounced when focusing only on the high use summer months of July and August. In these two months, participants reduced their energy use by 2.8% in 2008 and then managed to achieve a reduction of 3.5% in 2009. The ability to easily adjust their air-conditioning use, which is typically the largest electric use in homes during these months, is likely to be the cause of these higher summer month savings. Figure 4.3 shows average kWh use for these two months.

Figure 4-3. Average kWh per Customer for July and August



It is of interest to note that savings increased in the second year even while the months of May through August in 2009 were slightly cooler than the same months in 2008.

4.3 Differential Effect of Heating/Cooling Degree Days on Treatment and Control Households

Parameter estimates derived from the baseline LR model (10) are presented in Table 4-5, and estimates of the same parameters derived from the baseline DLFE model (11) are presented in Table 4.6.

Parameter estimates are interpreted as the marginal effect of a change in the variable on energy use. So, for instance, the LR model indicates that a 1-unit increase in heating degrees days per day increases average daily consumption of energy by .739 Kwh, while the DLFE model indicates such a change would increase average daily consumption by .730 Kwh.

The models are in good agreement with regard to the average daily treatment effect (see equation (12)). The LR model indicates that on a day free of heating and cooling degree days, the treatment reduces consumption of energy by 0.448 Kwh; each heating degree day adds 0.0182 to the savings, and each cooling degree day adds 0.0498 to the savings. These figures for the DLFE model are 0.326, 0.0245, and 0.0675, respectively. In the DLFE model, all treatment terms are significant at the .01 level. Estimates of the treatment effects in the LR model are less precise; the treatment terms $Treatment_k{\cdot}Post_t$ and $CDDd_t{\cdot}Treatment_k{\cdot}Post_t$ are significant at the .05 level, and the treatment term $HDDd_t{\cdot}Treatment_k{\cdot}Post_t$ is significant at the .08 level.

Table 4-5. Parameter estimates using the baseline Linear Regression (LR) Model (Dependent variable: Average daily Kwh; treatment terms shaded)

Variable	*Parameter estimate*	*Standard error*	*t-statistic*
Intercept	20.03454	0.05397	371.24
$Treatment_k$	-0.34995	0.08422	-4.16
$Post_t$	1.01504	0.08935	11.36
$Treatment_k{\cdot}Post_t$	-0.44838	0.13928	-3.22
$HDDd_t$	0.73943	0.00393	188.39
$HDDd_t{\cdot}Post_t$	-0.06662	0.00664	-10.04
$HDDd_t{\cdot}Treatment_k$	0.00277	0.00612	0.45
$HDDd_t{\cdot}Treatment_k{\cdot}Post_t$	-0.01815	0.01036	-1.75
$CDDd_t$	2.49685	0.01061	235.42
$CDDd_t{\cdot}Post_t$	-0.30645	0.01588	-19.3
$CDDd_t{\cdot}Treatment_k$	-0.03342	0.01652	-2.02
$CDDd_t{\cdot}Treatment_k{\cdot}Post_t$	-0.04983	0.0247	-2.02

Table 4-6. Parameter estimates using the baseline Differenced Linear Fixed Effects (DLFE) model (Dependent variable: Average daily Kwh)

Variable	*Parameter estimate*	*Standard error*	*t-statistic*
$Post_t$	-0.13361	0.04369	-3.06
$Treatment_k \cdot Post_t$	-0.32591	0.0681	-4.79
$HDDd_t$	0.73034	0.00192	380.76
$HDDd_t \cdot Post_t$	-0.01074	0.00324	-3.31
$HDDd_t \cdot Treatment_k$	0.0041	0.00299	1.37
$HDDd_t \cdot Treatment_k \cdot Post_t$	-0.02453	0.00506	-4.85
$CDDd_t$	2.44219	0.00518	471.24
$CDDd_t \cdot Post_t$	-0.16486	0.00776	-21.24
$CDDd_t \cdot Treatment_k$	-0.02305	0.00807	-2.86
$CDDd_t \cdot Treatment_k \cdot Post_t$	-0.06754	0.01208	-5.59

4.4 Extending the Analysis: The Effect of Housing Characteristics and Treatment Variables on Energy Savings

To the baseline models we added the following housing characteristics to examine the effect of these characteristics on energy savings under treatment:

- A binary variable indicating the presence of a pool ($Pool_k$ takes a value of 1 if household k has a pool, and 0 otherwise;
- A binary variable indicating the presence of a spa (Spa_k takes a value of 1 if household k has a spa, and 0 otherwise;
- An interaction term multiplying a binary variable indicating the presence of electric heat ($Eheat_k$ takes a value of 1 if household k has electric heat, and 0 otherwise) by the heating degree days per day, $HDDd_t$;
- Square footage of the residence ($Sqft_k$), measured in units of 100 square feet;
- Age of the residence (Age_k) measured in years; and
- The assessed value of the property ($Value_k$) measured in \$10,000 of assessed value.

A number of household characteristics for which data was available (income, age of head of household, number of household members, length of residence) were excluded from the analysis because preliminary analyses indicated these variables did not affect the treatment response and because using these variables would significantly reduce the sample size.

We also included in estimation two treatment variables: $Template_k$ is a binary variable taking a value of 1 if a household is assigned a “graphical” presentation of information and 0 for the “narrative” presentation of information. $Envelope_k$ is a binary variable taking a value of 1 if a household receives its material in a large (6x9) envelope and a 0 if it receives its material in a regular business envelope.

Results are presented in Table 4-7 (LR model) and Table 4-8 (DLFE model). As in the baseline models, coefficients reflect the marginal effect of the characteristic on average daily consumption of Kwh. So, for instance, results from the LR model indicate that a 100-ft^2 increase in the size of a residence increases average daily consumption of Kwh by 0.772; a pool increases average daily Kwh use by 10.90 Kwh.

In the LR model, the only housing characteristics that have a statistically significant effect on energy savings under the program are the presence of a pool and the value of the residence, though as a practical matter the effect of the latter is minor (a $10,000 increase in home value increases savings by 0.077 Kwh/day. The other housing characteristics examined in the analysis—Spa_k, $Eheat_k$, $Sqft_k$, and Age_k — were not statistically significant at the .05 alpha level.

In the DLFE model (Table 4-8), the only housing characteristic affecting energy savings is the presence of a pool. The upshot of the analysis is that except for the presence/absence of a pool, it is difficult to forecast savings under the treatment program based on housing characteristics.

Finally, neither model predicts that energy savings under the program is affected by the treatment variables $Envelope_k$ and $Template_k$.

Table 4-7. Parameter estimates using the extended Linear Regression (LR) Model (Dependent variable: Average daily Kwh; terms affecting treatment response are shaded)

Variable	*Parameter estimate*	*Standard error*	*t-statistic*
Intercept	2.58923	0.08741	29.62
$Treatment_k$	1.16059	0.13963	8.31
$Post_t$	1.4126	0.14112	10.01
$Treatment_k \cdot Post_t$	-0.1095	0.22251	-0.49
$HDDd_t$	0.42534	0.00334	127.39
$HDDd_t \cdot Post_t$	-0.03041	0.00564	-5.39
$HDDd_t \cdot Treatment_k$	-0.00836	0.00522	-1.6
$HDDd_t \cdot Treatment_k \cdot Post_t$	-0.01879	0.00882	-2.13
$CDDd_t$	2.47496	0.00872	283.91
$CDDd_t \cdot Post_t$	-0.25433	0.01305	-19.49
$CDDd_t \cdot Treatment_k$	-0.02555	0.01358	-1.88
$CDDd_t \cdot Treatment_k \cdot Post_t$	-0.06357	0.02031	-3.13
$Pool_k$	10.90364	0.04539	240.25

$Pool_k \cdot Post_t$	0.01959	0.07028	0.28
$Pool_k \cdot Treatment_k$	-0.12378	0.07189	-1.72
$Pool_k \cdot Treatment_k \cdot Post_t$	-0.69719	0.1114	-6.26
Spa_k	0.7963	0.09075	8.78
$Spa_k \cdot Post_t$	0.03275	0.14022	0.23
$Spa_k \cdot Treatment_k$	0.40093	0.14198	2.82
$Spa_k \cdot Treatment_k \cdot Post_t$	-0.31411	0.21966	-1.43
$Eheat_k$	1.26684	0.00345	367.46
$Eheat_k \cdot Post_t$	-0.06718	0.00586	-11.46
$Eheat_k \cdot Treatment_k$	-0.02382	0.00534	-4.46
$Eheat_k \cdot Treatment_k \cdot Post_t$	-0.01397	0.00909	-1.54
$Sqft_k$	0.7717	0.00371	208.24
$Sqft_k \cdot Post_t$	-0.02808	0.00575	-4.88
$Sqft_k \cdot Treatment_k$	-0.03334	0.0059	-5.65
$Sqft_k \cdot Treatment_k \cdot Post_t$	-0.01467	0.00916	-1.6
Age_k	-0.00408	0.00102	-4.02
$Age_k \cdot Post_t$	-0.0167	0.00158	-10.57
$Age_k \cdot Treatment_k$	-0.01144	0.00158	-7.24
$Age_k \cdot Treatment_k \cdot Post_t$	0.00116	0.00246	0.47
$Value_k$ (per $10,000)	0.07725	0.00143	54.04
$Value_k \cdot Post_t$	0.0142	0.00222	6.4
$Value_k \cdot Treatment_k$	-0.00981	0.00228	-4.31
$Value_k \cdot Treatment_k \cdot Post_t$	0.00636	0.00354	1.8
$Envelope_k \cdot Treatment_k$	0.02942	0.04088	0.72
$Envelope_k \cdot Post_t$	0.06717	0.04043	1.66
$Envelope_k \cdot Treatment_k \cdot Post_t$	-0.1137	0.07544	-1.51
$Template_k \cdot Treatment_k$	-0.18351	0.04088	-4.49
$Template_k \cdot Post_t$	-0.06236	0.04043	-1.54
$Template_k \cdot Treatment_k \cdot Post_t$	0.07479	0.07543	0.99

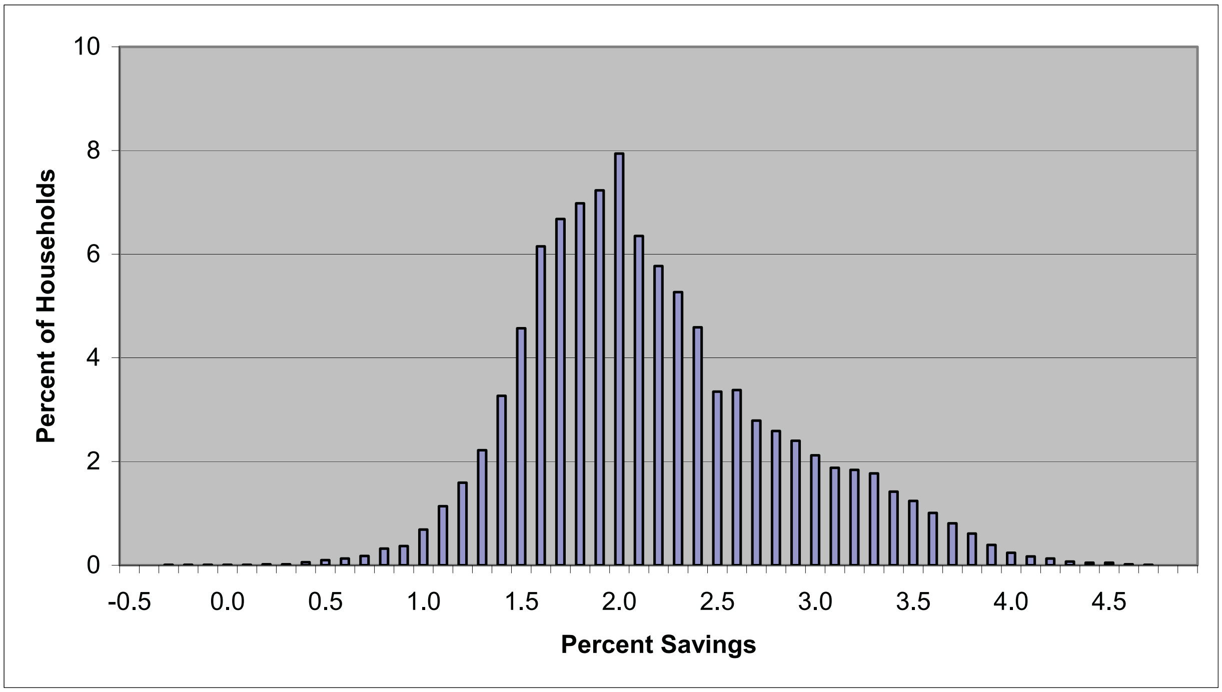
Table 4-8. Parameter estimates using the extended Differenced Linear Fixed Effects (DLFE) Model (Dependent variable: Average daily Kwh; terms affecting treatment response are shaded)

Variable	*Parameter estimate*	*Standard error*	*t-statistic*
$Post_t$	-2.39049	0.35686	-6.7
$Treatment_k \cdot Post_t$	-0.72654	0.55769	-1.3
$HDDd_t$	0.73135	0.00806	90.68
$HDDd_t \cdot Post_t$	-0.14781	0.01402	-10.54
$HDDd_t \cdot Treatment_k$	0.00426	0.01258	0.34
$HDDd_t \cdot Treatment_k \cdot Post_t$	-0.0348	0.02191	-1.59
$CDDd_t$	2.44438	0.02179	112.18
$CDDd_t \cdot Post_t$	-0.16331	0.03263	-5.01
$CDDd_t \cdot Treatment_k$	-0.0234	0.03395	-0.69
$CDDd_t \cdot Treatment_k \cdot Post_t$	-0.06932	0.05077	-1.37
$Pool_k \cdot Post_t$	0.37842	0.1758	2.15
$Pool_k \cdot Treatment_k \cdot Post_t$	-0.67809	0.27869	-2.43
$Spa_k \cdot Post_t$	-0.36664	0.35071	-1.05
$Spa_k \cdot Treatment_k \cdot Post_t$	-0.06743	0.54948	-0.12
$Eheat_k \cdot Post_t$	0.55903	0.01316	42.46
$Eheat_k \cdot Treatment_k \cdot Post_t$	0.00447	0.02041	0.22
$Sqft_k \cdot Post_t$	0.03128	0.01438	2.18
$Sqft_k \cdot Treatment_k \cdot Post_t$	0.02671	0.02289	1.17
$Age_k \cdot Post_t$	0.03545	0.00392	9.04
$Age_k \cdot Treatment_k \cdot Post_t$	0.00223	0.0061	0.36
$Value_k \cdot Post_t$	0.01346	0.00555	2.42
$Value_k \cdot Treatment_k \cdot Post_t$	0.00542	0.00887	0.61
$Envelope_k \cdot Post_t$	0.0192	0.13202	0.15
$Envelope_k \cdot Treatment_k \cdot Post_t$	-0.04618	0.20694	-0.22
$Template_k \cdot Post_t$	0.03245	0.13201	0.25
$Template_k \cdot Treatment_k \cdot Post_t$	-0.04626	0.20692	-0.22

4.5 Predicted Distribution of Savings in the Treatment Group

Using the LR model of the previous section, the predicted distribution of savings within the treatment group is presented in Figure 4-4. As noted previously, the average savings is about 2.2%. Predicted percent savings for 50% of all households lie in the interval {1.6, 2.2}, predicted savings for 80% of all households lie in the interval {1.4, 2.9}, and predicted savings for 95% of all households lie in the interval {1.1, 3.5}.

Figure 4-4. Frequency distribution of predicted percent annual energy savings (2007 as base year) within the treatment group



This distribution curve shows that savings are predicted for virtually all individuals, rather than being possible for just a small subset of customers with particular characteristics. It is important to emphasize that this frequency distribution describes *expected* savings within the sample, *conditional* on observed housing characteristics such as square footage of the residence, the presence/absence of a pool, the assessed value of the residence, and so forth, based on the point estimates of the OLS regression of method 2. For a given set of housing characteristics, some households in the real world will generate greater savings and some less than indicated in this modeled distribution.

4.6 Energy Savings of Treatment Households Receiving Monthly Versus Quarterly Reports

A treatment variable not included in the above analysis was the frequency of reports (monthly vs. quarterly) sent to treatment households. This is because the experimental design targeted households with relatively high energy use for monthly reports, and so including this variable would confound the estimated effects of housing characteristics correlated with high energy use.

To examine seasonal impacts by frequency of reporting, we ran the seasonal difference in difference model of Table 4-1 separately for households receiving monthly reports and households receiving quarterly reports. Control households were designated for the different report frequencies based on their level of use to properly match the participant groups. Results are presented in Table 4-9.

Table 4-9. Comparison of Impacts by Season and Frequency of Reports

Method	*Summer Impact*	*Winter Impact*	*Shoulder Months Impact*	*Annual Impact*
Monthly Reports (High Use Customers)	-2.8%	-2.3%	-1.9%	-2.3%
Quarterly Reports (Low Use Customers)	-1.4%	-1.6%	-1.4%	-1.6%
Overall	-2.6%	-2.2%	-1.7%	-2.2%

Low use customers receiving quarterly reports show relatively consistent savings throughout the seasons, with slightly higher savings in winter. High use customers receiving monthly reports reflect the overall pattern of savings, showing greatest savings in summer and lowest savings in the shoulder months.

5 AUTHOR BIOGRAPHIES

Daniel Violette, Ph. D. -- Dr. Violette is a Principal with Summit Blue Consulting who has over 20 years of experience in the energy industry. He is a founder and former CEO of Summit Blue and also served as a Vice President and Director with Hagler Bailly Consulting for over 10 years. He has also held officer-level positions with other major companies including serving as a Sr. Vice President with XENERGY, Inc., an energy services company, and with the Management Consulting Services Business Unit of Electronic Data Systems (EDS), one of the largest worldwide management services and technology companies.

Dr. Violette has managed many complex projects resulting in recommendations to senior management regarding actions to be taken related to demand response (DR), pricing and rates, resource planning, and energy efficiency. Current projects include several multi-year efforts examining the role of energy efficiency (EE) and DR in resource planning and development of integrated resource plans that address risk and uncertainty. He also has completed projects for the International Energy Agency on the value of EE and DR in resource planning including hedge/option values and risk management of system costs with a dozen US utilities and 20 countries, and he has authored a report for the Demand Response Research Center (CEC) on an integrated framework for assessing energy efficiency and DR. He is well known for his years of work on demand-side issues including planning, design, evaluation and integration. Dr. Violette has presented testimony and served on expert panels in over 25 regulatory jurisdictions in North America.

Bill Provencher, Ph.D. – Dr. Provencher serves as a full professor in the Department of Agriculture and Applied Economics at the University of Wisconsin-Madison. His published work has two distinct emphases: the dynamic allocation of resources and the valuation of nonmarket goods and services. His current research program focuses on three areas: a) the development of discrete choice models of the consumption of nonmarket goods and services; b) the interaction between socioeconomic and ecological systems; and c) dynamic issues in resource allocation, with attention focused mainly on using statistical methods to recover the dynamic behavior of resource owners. He has served on the board of the Association of Environmental and Resource Economists (AERE), co-edited and served on the editorial council of the *Journal of Environmental Economics and Management* (JEEM), and is currently on the editorial board of *Land Economics*. Dr. Provencher received an undergraduate degree in natural resources at Cornell University, an M.S. degree in forestry at Duke University in 1985, and a Ph.D. in agricultural economics from UC-Davis in 1991.

Mary Klos – Ms. Klos is a Senior Consultant at Summit Blue and has over 20 years of experience in the energy industry. Currently, she leads projects focused on impact analysis of energy efficiency and demand response programs. In her time at the Wisconsin Public Service Corporation, Ms. Klos worked consistently with energy efficiency and demand response issues from a variety of positions, including load forecasting, market research and demand-side management planning. She has worked with generation planners, transmission and distribution planners, rate design experts and marketing professionals to develop an integrated view of the entire DSM effort, and she has testified in rate proceedings and integrated resource planning dockets. Ms. Klos earned a BA in Economics from Beloit College and a Masters in Business Administration from the University of Wisconsin. Ms. Klos is also a certified Statistical Analysis System (SAS) Base Programmer.

APPENDIX A:

DETAILED MODEL RESULTS

Method 2: Linear Regression Base Model

The REG Procedure
Model: OrigOLS
Dependent Variable: AveDailyKWH

Number of Observations Read	2029885
Number of Observations Used	2029885

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	11	46553310	4232119	14082	<.0001
Error	2.03E+06	610043717	300.53295		
Corrected Total	2.03E+06	656597027			

Root MSE	17.33589	**R-Square**	0.0709
Dependent Mean	31.07693	**Adj R-Sq**	0.0709
Coeff Var	55.78378		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	**1**	20.03454	0.05397	371.24	<.0001
hddD	**1**	0.73943	0.00393	188.39	<.0001
cddD	**1**	2.49685	0.01061	235.42	<.0001
Post	**1**	1.01504	0.08935	11.36	<.0001
PosthddD	**1**	-0.06662	0.00664	-10.04	<.0001
PostcddD	**1**	-0.30645	0.01588	-19.3	<.0001
ParticPost	**1**	-0.44838	0.13928	-3.22	0.0013
ParticPosthddD	**1**	-0.01815	0.01036	-1.75	0.0796
ParticPostcddD	**1**	-0.04983	0.0247	-2.02	0.0437
Partic	**1**	-0.34995	0.08422	-4.16	<.0001
PartichddD	**1**	0.00277	0.00612	0.45	0.6505
ParticcddD	**1**	-0.03342	0.01652	-2.02	0.0431

Method 3: Fixed Effects Base Model

The REG Procedure
Model: base
Dependent Variable: diffaveDailykWh

Number of Observations Read	2029885
Number of Observations Used	2029885

Note: No intercept in model. R-Square is

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	10	46287941	4628794	64523.2	<.0001
Error	2.03E+06	145619983	71.7384		
Uncorrected Total	2.03E+06	191907924			

Root MSE	8.46985	**R-Square**	0.2412
Dependent Mean	1.80E-17	**Adj R-Sq**	0.2412
Coeff Var	4.71E+19		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
diffcddD	**1**	2.44219	0.00518	471.24	<.0001
diffhddD	**1**	0.73034	0.00192	380.76	<.0001
diffPost	**1**	-0.13361	0.04369	-3.06	0.0022
diffPosthddD	**1**	-0.01074	0.00324	-3.31	0.0009
diffPostcddD	**1**	-0.16486	0.00776	-21.24	<.0001
diffParticPost	**1**	-0.32591	0.0681	-4.79	<.0001
diffParticPosthddD	**1**	-0.02453	0.00506	-4.85	<.0001
diffParticPostcddD	**1**	-0.06754	0.01208	-5.59	<.0001
diffParticHDDd	**1**	0.0041	0.00299	1.37	0.1704
diffParticCDDd	**1**	-0.02305	0.00807	-2.86	0.0043

Method 2: Linear Regression
Expanded Model

The REG Procedure
Model: HeterOLS
Dependent Variable: AveDailyKWH

Number of Observations Read	2029885
Number of Observations Used	2025212
Number of Observations with Missing Values	4673

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	41	245023876	5976192	29501.5	<.0001
Error	2.03E+06	410244298	202.57277		
Corrected Total	2.03E+06	655268174			

Root MSE	14.23281	**R-Square**	0.3739
Dependent Mean	31.09019	**Adj R-Sq**	0.3739
Coeff Var	45.7791		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	2.58923	0.08741	29.62	<.0001
Post	1	1.4126	0.14112	10.01	<.0001
ParticPost	1	-0.1095	0.22251	-0.49	0.6226
Partic	1	1.16059	0.13963	8.31	<.0001
cddD	1	2.47496	0.00872	283.91	<.0001
PostcddD	1	-0.25433	0.01305	-19.49	<.0001
ParticPostcddD	1	-0.06357	0.02031	-3.13	0.0017
ParticcddD	1	-0.02555	0.01358	-1.88	0.0599
hddD	1	0.42534	0.00334	127.39	<.0001
PosthddD	1	-0.03041	0.00564	-5.39	<.0001
ParticPosthddD	1	-0.01879	0.00882	-2.13	0.0331
ParticHddD	1	-0.00836	0.00522	-1.6	0.109
pool	1	10.90364	0.04539	240.25	<.0001
PostPool	1	0.01959	0.07028	0.28	0.7805
ParticPostPool	1	-0.69719	0.1114	-6.26	<.0001
ParticPool	1	-0.12378	0.07189	-1.72	0.0851
spa	1	0.7963	0.09075	8.78	<.0001
PostSpa	1	0.03275	0.14022	0.23	0.8153
ParticPostSpa	1	-0.31411	0.21966	-1.43	0.1527
ParticSpa	1	0.40093	0.14198	2.82	0.0047
ElecHeatHDDd	1	1.26684	0.00345	367.46	<.0001
PostElecHeatHDDd	1	-0.06718	0.00586	-11.46	<.0001
ParticPostElecHeatHDDd	1	-0.01397	0.00909	-1.54	0.1243
ParticElecHeatHDDd	1	-0.02382	0.00534	-4.46	<.0001
sqft_00	1	0.7717	0.00371	208.24	<.0001
PostSqft_00	1	-0.02808	0.00575	-4.88	<.0001
ParticPostSqft_00	1	-0.01467	0.00916	-1.6	0.1094
ParticSqft_00	1	-0.03334	0.0059	-5.65	<.0001
age	1	-0.00408	0.00102	-4.02	<.0001
Postage	1	-0.0167	0.00158	-10.57	<.0001
ParticPostAge	1	0.00116	0.00246	0.47	0.6359
Particage	1	-0.01144	0.00158	-7.24	<.0001
house_value_0000	1	0.07725	0.00143	54.04	<.0001
Posthouse_value_0000	1	0.0142	0.00222	6.4	<.0001
ParticPostHouse_value_0000	1	0.00636	0.00354	1.8	0.0724
Partichouse_value_0000	1	-0.00981	0.00228	-4.31	<.0001
PostTemplate	1	-0.06236	0.04043	-1.54	0.123
ParticPostTemplate	1	0.07479	0.07543	0.99	0.3214
ParticTemplate	1	-0.18351	0.04088	-4.49	<.0001
PostEnvelope	1	0.06717	0.04043	1.66	0.0967
ParticPostEnvelope	1	-0.1137	0.07544	-1.51	0.1318
ParticEnvelope	1	0.02942	0.04088	0.72	0.4718

Method 3: Fixed Effects Expanded Model

The REG Procedure
Model: HeterDF
Dependent Variable: AveDailyKWH

Number of Observations Read	2029885
Number of Observations Used	2025212
Number of Observations with Missing Values	4673

Note: No intercept in model. R-Square is redefined.

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	26	50192832	1930494	1525.61	<.0001
Error	2.03E+06	2562644528	1265.38724		
Uncorrected Total	2.03E+06	2612837360			

Root MSE	35.57228	**R-Square**	0.0192
Dependent Mean	31.09019	**Adj R-Sq**	0.0192
Coeff Var	114.41643		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
diffPost	1	-2.39049	0.35686	-6.7	<.0001
diffParticPost	1	-0.72654	0.55769	-1.3	0.1927
diffcddD	1	2.44438	0.02179	112.18	<.0001
diffPostcddD	1	-0.16331	0.03263	-5.01	<.0001
diffParticPostcddD	1	-0.06932	0.05077	-1.37	0.1721
diffParticCDDd	1	-0.0234	0.03395	-0.69	0.4906
diffhddD	1	0.73135	0.00806	90.68	<.0001
diffPosthddD	1	-0.14781	0.01402	-10.54	<.0001
diffParticPosthddD	1	-0.0348	0.02191	-1.59	0.1122
diffParticHDDd	1	0.00426	0.01258	0.34	0.7349
diffPostPool	1	0.37842	0.1758	2.15	0.0314
diffParticPostPool	1	-0.67809	0.27869	-2.43	0.015
diffPostSpa	1	-0.36664	0.35071	-1.05	0.2958
diffParticPostSpa	1	-0.06743	0.54948	-0.12	0.9023
diffPostElecHeatHDDd	1	0.55903	0.01316	42.46	<.0001
diffParticPostElecHeatHDDd	1	0.00447	0.02041	0.22	0.8267
diffPostSqft_00	1	0.03128	0.01438	2.18	0.0296
diffParticPostSqft_00	1	0.02671	0.02289	1.17	0.2434
diffPostAge	1	0.03545	0.00392	9.04	<.0001
diffParticPostAge	1	0.00223	0.0061	0.36	0.7151
diffPostHouse_Value_0000	1	0.01346	0.00555	2.42	0.0154
diffParticPostHouse_Value_0000	1	0.00542	0.00887	0.61	0.5411
diffPostTemplate	1	0.03245	0.13201	0.25	0.8058
diffParticPostTemplate	1	-0.04626	0.20692	-0.22	0.8231
diffPostEnvelope	1	0.0192	0.13202	0.15	0.8844
diffParticPostEnvelope	1	-0.04618	0.20694	-0.22	0.8234

Base Model for Quarterly Report
Group

The REG Procedure
Model: Qtrly
Dependent Variable: diffaveDailykWh

Number of Observations Read	240168
Number of Observations Used	240168

Note: No intercept in model. R-Square is redefined.

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	5	1901600	380320	19722.3	<.0001
Error	240163	4631247	19.28376		
Uncorrected Total	240168	6532846			

Root MSE	4.39133	**R-Square**	0.2911
Dependent Mean	-4.51E-18	**Adj R-Sq**	0.2911
Coeff Var	-9.73E+19		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
diffPost	**1**	0.30321	0.05111	5.93	<.0001
diffcddD	**1**	1.39007	0.00593	234.31	<.0001
diffPostcddD	**1**	-0.09566	0.00897	-10.66	<.0001
diffhddD	**1**	0.34707	0.0022	157.56	<.0001
diffPosthddD	**1**	-0.00083494	0.00378	-0.22	0.8253

Covariance of Estimates					
Variable	**diffPost**	**diffcddD**	**diffPostcddD**	**diffhddD**	**diffPosthddD**
diffPost	0.002612615	0.000141865	-0.000385561	5.94168E-05	-0.000172727
diffcddD	0.000141865	3.51952E-05	-0.000035206	9.21E-06	-9.21E-06
diffPostcddD	-0.000385561	-0.000035206	8.04653E-05	-9.21E-06	2.53404E-05
diffhddD	5.94168E-05	9.21E-06	-9.21E-06	4.85E-06	-4.86E-06
diffPosthddD	-0.000172727	-9.21E-06	2.53404E-05	-4.86E-06	1.43038E-05

Base Model for Monthly Report
Group

The REG Procedure
Model: Month
Dependent Variable: diffaveDailykWh

Number of Observations Read	586698
Number of Observations Used	586698

Note: No intercept in model. R-Square is redefined.

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	5	18214496	3642899	40555.2	<.0001
Error	586693	52700128	89.82573		
Uncorrected Total	586698	70914624			

Root MSE	9.47764	**R-Square**	0.2569
Dependent Mean	3.17E-17	**Adj R-Sq**	0.2568
Coeff Var	2.99E+19		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
diffPost	**1**	-0.56019	0.06894	-8.13	<.0001
diffcddD	**1**	2.84333	0.00824	345.22	<.0001
diffPostcddD	**1**	-0.31349	0.01225	-25.59	<.0001
diffhddD	**1**	0.89418	0.00305	292.81	<.0001
diffPosthddD	**1**	-0.0613	0.00514	-11.93	<.0001

Covariance of Estimates					
Variable	**diffPost**	**diffcddD**	**diffPostcddD**	**diffhddD**	**diffPosthddD**
diffPost	0.004752634	0.000276504	-0.000708873	0.000114856	-0.000314899
diffcddD	0.000276504	6.78382E-05	-0.000067851	1.77594E-05	-0.000017764
diffPostcddD	-0.000708873	-0.000067851	0.000150131	-0.000017762	4.66113E-05
diffhddD	0.000114856	1.77594E-05	-0.000017762	9.33E-06	-9.33E-06
diffPosthddD	-0.000314899	-0.000017764	4.66113E-05	-9.33E-06	2.63913E-05

NON-CONFIDENTIAL

Request IR-13:

Please provide information with regards to the number of participants in the planned Home Energy Report pilot study.

Response IR-13:

The 2012 DSM Plan projects approximately 65,000 participants in the Home Energy Report pilot.

NON-CONFIDENTIAL

Request IR-14:

Many/most jurisdictions using OPower utilities are claiming a one year measure life. This yields large annual savings, but much smaller lifetime savings and net benefits. Has ENSC considered this factor in the formulation of the Home Energy Report pilot?

Response IR-14:

Yes. ENSC has assumed a one-year measure life for annual savings from the Home Energy Report pilot. The associated lifetime savings and net benefits reflect a one-year measure life.

NON-CONFIDENTIAL

Request IR-15:

Please explain how and why commercial & industrial programs are expected to achieve 32% greater GWh savings with 4% ($800,000) more budget than residential programs budget and savings projections.

Response IR-15:

The projected higher yield, in terms of energy savings per cost for the C&I programs compared to the residential programs, is due to the different mix of measures, hours of measure operation per year, program strategies and associated program incentive and non-incentive cost structures in each sector. In general, C&I programs include measures that save more energy per program expenditure.

NON-CONFIDENTIAL

Request IR-16:

Please express on a sector basis, what percentage of sales the projected 2012 energy savings represent.

Response IR-16:

The projected 2012 energy savings in the residential sector are approximately 1.17 percent of residential sector sales.

The projected 2012 energy savings in the nonresidential sector are approximately 1.56 percent of commercial and industrial sector sales, excluding the Extra Large Industrial sector.

NON-CONFIDENTIAL

Request IR-17:

Please provide any information with respect to ENSC protocols for dealing with cumulative over-achievement and/or unexpected savings from outside of ENSC and how this relates to annual DSM planning. Please also provide a comparison of under/over achievement of cumulative savings vs. planning for annual savings, specific to the 2012 annual savings projections.

Response IR-17:

Over-achievement or under-achievement of energy savings associated with a given year's DSM Plan implementation, once evaluated and verified, will be accounted for in the development of the next DSM Plan to be filed with the UARB.

Significant and verifiable energy savings occurring from activities outside DSM programs are also accounted for in DSM Plan development. This is consistent with the 2009 IRP Update, which states in Appendix D, Attachment 1, page 50, that:

> "All DSM is assumed to be included in the projection used in the 2009 IRP. This encompasses conservation efforts and investments occurring inside and outside of customer funded DSM programs, including:
>
> - consumer behaviour and investments
> - energy efficiency codes and standards
> - other agencies
> - NSPI, and
> - DSM Administrator"

Figure 4.2 on page 12 of ENSC's Evidence on the 2012 DSM Plan shows a comparison of the cumulative energy and demand savings targets vs. the savings results and/or projections from 2008 to 2012.

NON-CONFIDENTIAL

Request IR-18:

Should over achievement in a prior year reduce goals and investment in a current year. If so, why?

Response IR-18:

Evaluated and verified over-achievement or, as the case may be, under-achievement of energy and demand savings from a given year of DSM activity, should be accounted for in the development of future year DSM Plans to retain consistency with the cumulative long term savings goals identified through the Integrated Resource Planning process.

NON-CONFIDENTIAL

Request IR-19:

Changes to DSM Screening (p.17)

Please further explain why changes to the DSM Screening to TRC and PAC are important to the programming evaluation procedures at ENSC and how this will translate to furthering DSM in Nova Scotia.

Response IR-19:

Please refer to Avon IR-3a.

NON-CONFIDENTIAL

Request IR-20:

The overall purpose of electricity DSM programs in Nova Scotia is to help meet the province's long-term electricity needs through conservation and energy efficiency as a lower cost alternative to supply. More specifically, DSM spending is aimed at meeting the overall DSM savings set out in the IRP. The IRP has shown that DSM is the lowest cost option available to meet the province's future electricity needs while respecting provincial emissions targets and renewable energy requirements. (p.20)

Please explain if more energy savings are achievable in ENSC programs for the residential and commercial & industrial sectors to assist with the overall purpose of DSM in Nova Scotia, with respect to the issue of unexpected savings from ELI and changes to any prior DSM plan for 2012.

Response IR-20:

Please refer to EAC IR-22, Attachment 1, Slide 51.

NON-CONFIDENTIAL

Request IR-21:

Please provide an estimate of the cost of procurement for additional energy savings from in ENSC programs for the residential and commercial & industrial sectors, with respect to the issue of unexpected savings from ELI and changes to any prior DSM plan for 2012.

Response IR-21:

Please refer to EAC IR-22, Attachment 1, Slide 51.

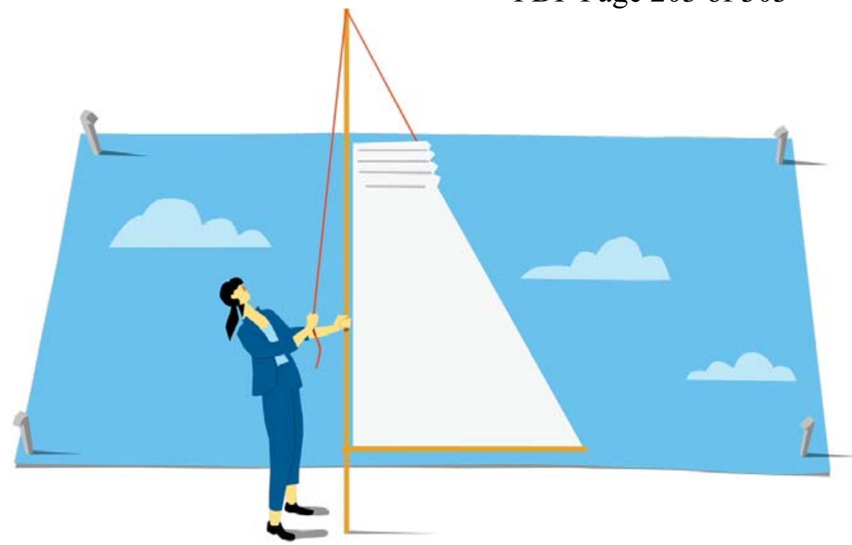
NON-CONFIDENTIAL

Request IR-22:

Please produce the entire presentation given to stakeholders on January 7, 2011 by Stu Slote from Navigant Consulting entitled 'ENSC 2012 DSM Plan: Programs Outline".

Response IR-22:

Please refer to Attachment 1.



Efficiency Nova Scotia 2012 DSM Plan: **Programs Outline**

Stu Slote
Associate Director
NAVIGANT

ENSC Stakeholder Conference
January 7, 2011

efficiency
NOVA SCOTIA CORPORATION

Agenda

Residential

1. Efficient Products
2. Existing Houses (includes fuel substitution, pilot in 2011)
3. Low Income Households (includes fuel substitution, pilot in 2011)
4. New Houses
5. Home Energy Report (new in 2012)

Commercial and Industrial

6. Prescriptive Rebate for Retrofit and New Construction (also includes Smart Lighting Choices)
7. Custom for Retrofit and New Construction (also includes fuel substitution, new in 2012)
8. Small Business Direct Install

Preliminary Budget / Energy Savings Projections

1. Residential – Efficient Products

- Launched in 2008

Targets

- Residential (and small commercial) customers
- Consumer sector sale / installation of energy efficient ENERGY STAR® products

Incentives for measures may include

- Lighting – CFLs and LEDs, lighting controls
- Appliances – washing machines, refrigerators, freezers, dehumidifiers
- Consumer electronics
- Power bars to facilitate reduction in standby loss
- Programmable thermostats for electric heating systems
- Turn-in of spare appliances (refrigerators, freezers)

1. Residential – Efficient Products (continued)

May employ third-party implementation contractor

- Build partnerships with retailers
- Work through upstream market channels
- Consumer marketing and education
- Work with regional or national alliances
- Target midstream market actors
- Work with bulk purchasers

2. Residential – Existing Houses

- Launched in 2009

Objective: promote comprehensive electrical energy efficiency (EE) improvements in existing homes / small multi-family buildings, including rental housing through

- Marketing / promotion of benefits of home EE improvements
- Provision of home energy assessments by qualified individuals
- Direct installation of certain measures by home energy assessors
- Home energy assessors directly install CFLs and low cost domestic hot water measures
- Financial assistance for measures

2. Residential – Existing Houses (continued)

Incentives

- Levels increased for some measures to compensate for lack of matching federal incentives
- Additional bonus offered for participants who achieve large savings
- Explore financing options

2. Residential – Existing Houses (continued)

Approaches

- Consider developing / maintaining list of qualified contractors
- Explore opportunities to target market to high-use households
- Pilot direct installation of additional measures by auditors, and standalone incentives for certain measures to maximize savings
- Contractors offered training in building science and key measures (air sealing)
- Include fuel substitution (pilot in 2011)

2. Residential – Existing Houses (continued)

Homes with electric space heating, incentives may be provided for envelope / heating system measures if cost-effective on site-specific basis

May include

- Comprehensive air-sealing to reduce building envelope leakage
- ENERGY STAR® windows and doors
- Insulation of attics, walls, crawl spaces and basements
- Upgrade of heating system to more efficient technology
- Fuel substitution to natural gas, biomass (cordwood or wood pellets)
- Electronic programmable thermostats
- Other custom, site-specific electric heat-saving measures

3. Residential – Low Income Households

- Launched in 2009
- Targets electrically-heated homes for weatherization / insulation upgrades at no cost to participants

Housing types

- Single detached
- Mobile / mini homes
- Duplexes
- Multi-family buildings
- Rental

Participant recruitment outreach

- Apartment building owner / managers
- Community / neighbourhood groups

3. Residential – Low Income Households (continued)

Two categories of EE upgrades

Scope I building envelope upgrades

- Infiltration reduction
- Insulating basements, crawl spaces, walls, attics
- Other building envelope work outside scope I may be proposed by contractors if work needs to be done to allow them to complete Scope I upgrades; work completed on case-by-case basis

Scope II measures

- CFLs
- Insulating electric water tank / hot water piping
- Low flow shower heads / faucet aerators
- Providing power bars / auto shut-off electric kettles
- Installing clothes lines
- Replacing eligible freezers / refrigerators with ENERGY STAR® appliances

3. Residential – Low Income Households (continued)

Funding

- For Scope I upgrades to electrically heated homes comes from electricity customers
- If home has both electric and non-electric heating, funding is proportional to estimated use of electric space heating
- For Scope II electric DSM upgrades, comes from electricity customers, for all homes regardless of heating source

- Home must be safe and accessible in order for contractors to perform upgrade
- Additional work may be done to allow for all Scope I upgrades to be completed
- Additional work is assessed on a case-by-case basis

3. Residential – Low Income Households (continued)

Approaches

- NS Dept of Community Services (DCS) and Service Nova Scotia and Municipal Relations (SNSMR) help market to qualifying low income individuals
- DCS and SNSMR pre-screen participants
- Income criteria used for electrically-heated homes is government's pre-tax, post transfer Low Income Cut-Off (LICO)
- Low Income Outreach Agents supplement efforts of DCS and SNSMR through in-field recruitment of participants who heat mainly with electricity
- Address multi-family sector issues unique to landlord / tenant situations through intervention strategies targeted toward each party
- Direct installation of measures provided to SF / MF low income renters

3. Residential – Low Income Households (continued)

Program covers electrical measures

- **Replacement**
  - incandescent lamps with CFLs
  - halogen with CFL torchieres
  - ceiling (flush mount) halogen with CFL compatible fixtures
  - broken or un-covered outdoor porch light fixtures to accommodate CFLs
  - LED night lights
  - primary refrigerator and stand-alone freezer
- Option of removal of second refrigerator, freezer, or window air-conditioner
- Provision of power bars to facilitate reduction in standby loss
- Installation of drain water heat recovery device
- Option of fuel substitution to natural gas, biomass (cordwood or wood pellets) or advanced heat pumps for space heat or domestic hot water
- Customer education (explanations, brochures, tip sheets)

3. Residential – Low Income Households (continued)

Envelope measures (homes with electric space heat or electric heat pumps)

- attic, wall, and basement insulation
- air sealing / weather stripping
- outside and storm door installation or replacement
- programmable thermostats
- faceplate gaskets

Hot water measures (homes with electric resistance hot water or heat pump water heater)

- tank wrap for electric hot water heater
- pipe wrap for exposed hot water pipes
- low flow showerheads / kitchen faucet aerators / bathroom faucet aerators

3. Residential – Low Income Households (continued)

Implementation

- Program employs Service Organizations / Energy Advisors, selected through competitive Request for Proposal (RFP) process
- Program implementation carried out by contracted Service Organizations
- Current implementation policies and procedures with Service Organizations could be modified as appropriate to further enhance implementation of cost-effective electrical EE measures

4. Residential – New Houses

- Launched in 2009

Objectives

- Encourage homebuilders to participate in EnerGuide for New Houses (EGNH) program
- Increase number of houses built to high levels of energy efficiency
- Increase number of new houses installing ENERGY STAR® labeled products
  - windows, heating systems, insulation, lighting, appliances, and other measures such as solar hot water heating, and drain-water heat recovery
- Promote non-electric fuel choice
- Encourage homebuilders to include additional energy efficient products not addressed by EGNH program
- Create greater market awareness of benefits of energy efficient new homes and generate greater market demand for EE construction
- Support establishment and growth of high performance residential new construction building community, and promote energy efficient design, building materials, equipment and building practices through training and education

4. Residential – New Houses (continued)

Approach

- Energy assessments, practical design advice provided to builders prior to construction
- Home rated on scale based on modeled energy performance
- Upon completion, final as-built inspection and rating is provided along with eligible financial incentives
- Require minimum EnerGuide rating above standard building code requirements

4. Residential – New Houses (continued)

Incentives for individual measures, packages of measures, and/or overall levels of building energy efficiency

Eligible Measures

- central / mini-split / ground source heat pump systems
- programmable thermostats
- drain water heat recovery
- solar domestic water heating
- electric water heater pipe wrap
- electric water heater tank wrap
- efficient light fixtures
- fuel choice to promote non-electric space heating and domestic hot water systems

5. Residential – Home Energy Report

New in 2012

Objectives

- Secure cost-effective electrical energy savings for residential customers by providing feedback on household energy consumption on energy bills, mailers, or in-home web displays
- Also indirectly supports participation in other ENSC programs

Approach

- Customers in targeted geographic locations receive feedback on energy bills and through direct mailers
- Residences within a region included so average energy benchmarks can be provided, allowing participants to see how they compare to neighbors, fostering a competitive spirit of conservation
- Control group used for comparison purposes does not receive report
- Households within some regions may be given the opportunity to enroll to receive real time feedback via in home displays

5. Residential – Home Energy Report (continued)

May also provide

- Recommendations for further action, including low-cost and investment-grade measures
- Referrals and promotion of relevant ENSC programs
- Additional analysis, for example based on usage disaggregation

5. Residential – Home Energy Report (continued)

Two primary feedback options

- On-bill report: feedback information integrated into NSPI bills
- Standalone report: feedback provided to customers separately from utility bills
  - May involve combination of mailed information and online tool available for customers
  - Third-party providers provide customizable packages

- ENSC will need to work with NSPI to implement
- Final format of and mechanism for customer feedback determined during 2011
- Smart Meter-Integrated Home Energy Report will be examined

5. Residential – Home Energy Report (continued)

Implementation

- Customers may be given option of completing on-line or mail-in questionnaire about their home, which will allow ENSC to provide more customized recommendations
- Program may be combined with other feedback campaigns
- Explore use of social media opportunities to enhance home energy report and / or retrofit campaigns, and may consider community-based approaches
- Explore working with municipal utilities and NSPI

5. Residential – Home Energy Report (continued)

Program naturally targets customer behavioural changes

- thermostat setback
- cold water for clothes washing
- use of clothes lines for drying
- switch off lights in unoccupied rooms
- can encourage deeper measures
- community-based component could conceivably include low-cost measures such as CFLs

5. Residential – Home Energy Report (continued)

Next steps

- Final program strategy determined during further design work in 2011, may pilot in 2011
- Delivery of core report component likely be contracted out to an existing third-party provider, and would require NSPI's collaboration for data collection
- Third-party provision being adopted by several Canadian jurisdictions, and privacy act (PIPEDA) concerns are being addressed

6. Commercial and Industrial – Prescriptive

Two distinct elements

- Business Energy Rebate (BER) provides prescriptive rebates (launched in 2010)
  - Cover 20-40% of equipment incremental costs
  - On-bill financing offered for remainder costs
  - Financing provided interest-free and repaid through 24 equal monthly payments on customer's Nova Scotia Power bill
- Smart Lighting Choices (SLC) upstream program for distributors for high performance T8 lamps and ballasts (launched in 2008)
  - Could pave way for future lighting standard
- Both elements focus on market-driven opportunities in natural replacement and new construction markets
- In 2012 current set of prescriptive measures expands to better support segment-specific effort

6. Commercial and Industrial – Prescriptive (continued)

Implementation

- Incentive for qualifying equipment or services for discretionary retrofit and market driven / new construction applications
- For key market segments, applicable technologies bundled together into single application package along with other program offerings
- Work through existing market channels to enhance competitiveness of high efficiency equipment and encourage adoption of targeted technologies
- Stimulate market provider investment in stocking and promoting efficient products through targeted outreach effort
- Train and equip market providers to convey energy and monetary savings benefits to consumers and communicate equipment eligibility requirements
- In 2012 investigate
  - qualified vendors program
  - opportunities to leverage market actors, via incentives or co-branding, to achieve low cost program promotion
  - Cross-marketing between BER and SLC (and Custom program)

6. Commercial and Industrial – Prescriptive (continued)

- Prescriptive measures can achieve savings in projects unable / unwilling to follow full New Construction Core Performance and / or Custom program approach
- Important opportunities for implementation in 2012
  - performance lighting incentives to reward better lighting design
  - prescriptive incentives based on aggressive lighting power density requirements
- Target equipment where unit electrical energy savings reliably predicted and standard per-measure savings (deemed savings) and incentive levels can be established
- Simplifies application process and reduces administrative costs
- Incentives and associated measures delivered through existing market channels

6. Commercial and Industrial – Prescriptive (continued)

Lighting

- compact fluorescent lamps (screw-in and pin-based fixtures)
- LED exit signs (retrofit only)
- high-performance T8 / T5 lamps, ballasts, and fixtures
- high-bay fluorescent fixtures
- pulse start metal halide lamps
- electronic dimming ballasts and bi-level ballasts
- occupancy sensors
- LED lighting technologies
  - traffic signals
  - street lights (customer-owned)
  - parking lot / parkade lighting
  - interior spot and flood lighting
  - others as applicable

6. Commercial and Industrial – Prescriptive (continued)

Heating Ventilation and Air Conditioning (HVAC)

- high efficiency packaged HVAC equipment (packaged terminal air-conditioners (PTAC), rooftop units)
- high efficiency chillers
- enthalpy and dry-bulb economizer controls for HVAC systems
- programmable thermostats
- reflective window films
- energy management systems (EMS)
- others as applicable

Drives

- Adding adjustable speed drives (ASD) for fans / pumps / motors

6. Commercial and Industrial – Prescriptive (continued)

Refrigeration

- controls for evaporative fan motors or door heaters
- zero energy doors
- high-efficiency evaporate fan motors
- floating head pressure controls
- discus or scroll compressors
- reach-in coolers or freezers
- premium efficiency ice makers
- free cooling with outdoor air
- economizer controls
- door gasket
- strip curtain
- automatic door closer
- others as applicable

6. Commercial and Industrial – Prescriptive (continued)

Compressed Air

- variable frequency drive for screw compressor
- air receiver / tanks for load / no-load compressor
- cycling refrigerated dryer
- no-loss drain
- air entraining air nozzle
- others as applicable

Vending Machine – controller

Water – drain water heat recovery systems

6. Commercial and Industrial – Prescriptive (continued)

Food Service

- convection, rack, and conveyor oven
- fryer
- griddle
- steam cooker
- holding cabinet
- solid and glass door refrigerators and freezer
- commercial ice machine
- demand-control, variable flow ventilation hood

Hospitality

- package terminal air conditioners and heat pump
- commercial pool and spa heater
- ozone laundry system
- vending machine controller
- commercial ice machine

6. Commercial and Industrial – Prescriptive (continued)

Agricultural and Food Processing

- low pressure sprinkler nozzles
- sprinkler to drip irrigation
- greenhouse heat curtains
- infrared film for greenhouses
- discus and scroll compressors
- pipe insulation
- tank insulation
- process boilers
- steam traps

7. Commercial and Industrial – Custom

Objectives

- secure cost-effective electrical energy savings from efficiency projects
- promote fuel choice in new construction
- fuel substitution in retrofits of existing non-residential facilities

Target

- Eligible retrofit projects save 20,000+ kWh/year
- Can aggregate multiple sites, where cost effectiveness is improved and incentives from other C&I programs do not apply

7. Commercial and Industrial – Custom (continued)

In 2012 introduce aggressive targeted segment-specific approach

- Package program services and incentives, both custom and prescriptive, to market segments with homogenous end uses
- Implementing targeted segment-specific approach involves no substantive change to incentive levels or structure
- Packaging measures, services, and technical and business expertise to each unique segment

7. Commercial and Industrial – Custom (continued)

Examples of segments to be targeted in 2012

- Schools, P-12 and colleges / universities
- Large multi-family buildings
- Government facilities
- Military installations
- High-tech industry
- Data centres
- Grocery stores

7. Commercial and Industrial – Custom (continued)

New construction and major renovation (launched mid-year 2010)

- Eligible for Custom program using one of two paths
  - Core Performance
    - most applicable to small and medium office, school, retail, warehouses
    - provides easy to follow standards for lighting, HVAC, and insulation
    - offers an Enhanced Performance Strategies option for greater savings in other building end uses
  - Whole Building
    - for projects not well suited to Core Performance path or that have to do energy modeling for another reason
    - offers study and custom implementation incentives for new buildings

Technical assistance through building owners, their agents, and design community

7. Commercial and Industrial – Custom (continued)

Market-driven measures

- planned equipment replacement
- new construction
- renovation
- expansion
- equipment replacement on burn-out

Discretionary retrofit

- Where equipment or building envelope components replaced prior to end of useful lives as cost-effective retrofit (aka early retirement)

7. Commercial and Industrial – Custom (continued)

Standard program technical / financial assistance components planned for 2012

- assisting customers in identifying and securing services of qualified third-party expertise
- providing incentives and rebates for initial scoping studies or audits of existing facilities, as well as detailed engineering assessments for specific retrofit projects
- providing funding support for technical assistance to achieve more efficient designs in new facilities and major renovation projects
- providing financial incentives for cost-effective electrical energy efficiency projects
- providing project financing through interest-free loans repayable through 24 equal monthly payments on customer's Nova Scotia Power bill

7. Commercial and Industrial – Custom (continued)

Important aspect of 2012 strategy is leveraging main components into customized offerings that address unique opportunities at customer facilities

Examples

- Compressed air audit initiative addressing entire delivery system and particularly operational opportunities
  - Combines feasibility study and technical assistance with prescriptive and custom rebates
  - Upgrades are often cost-effective, short-payback measures that may not command significant incentive dollars
  - Allows ‘foot in the door’ for marketing broader program
- Industrial processes / productivity initiative
  - Energy / unit produced based, to allow benchmarking against others within sector and ensure best in class efficiency

7. Commercial and Industrial – Custom (continued)

- Retro-commissioning services
  - provide technical assistance and incentives for optimizing energy usage of existing C&I equipment
- Support of continuous energy improvement initiatives for customers with industrial processes can be effective option for obtaining operational and retrofit savings
  - Can be delivered in cohort environment, where managers from similar industries meet together regularly, exchange technical support, and compare results, supported by industry-specific expertise

7. Commercial and Industrial – Custom (continued)

Eligible measures

- process optimization
- refrigeration upgrades
- compressed air upgrades
- monitoring and / or control systems
- HVAC system tune-ups
- fuel choice in new construction
- fuel substitution retrofits to natural gas, biomass energy (wood chips or pellets) or advanced heat pumps for space heat or domestic hot water
- Equipment / applications not addressed in other C&I programs

7. Commercial and Industrial – Custom (continued)

Approach

- Consider developing staff expertise and initiative design that differentiates among types of customers and segments
- For example, specialists for large energy users
- Different staff and approaches utilized for new construction versus existing buildings
- Differentiation of services between large and small projects
- Strategy would include deployment of specific technical specialists who can “speak the language” of specific industry

7. Commercial and Industrial – Custom (continued)

Strategies

- Consider using billing data, market analysis and customer segmentation to target customers with highest potential for outreach and recruitment
- Incentives negotiated based on amount determined to overcome incremental cost investment barriers for market-driven and new construction measures, and full-cost investment barrier for retrofits
- Actual incentive based on energy savings analysis

8. Commercial and Industrial – Small Business Direct Install

- Launched in 2008
- Targets non-residential customers with lighting and in 2012, commercial refrigeration load
- Eligibility thresholds
  - average peak monthly demand of < 100 kW or
  - annual electrical use < 300,000 kWh

8. Commercial and Industrial – Small Business Direct Install

Implementation

- Turnkey installation of comprehensive set of measures
- Although program will target customers with lighting and refrigeration loads, all energy saving opportunities will either be addressed by current comprehensive suite of measures, or identified for future program intervention
- Implementation contractors to identify and recruit eligible small businesses
- Installation contractors for direct install of lighting and refrigeration upgrades and disposal of old materials

8. Commercial and Industrial – Small Business Direct Install (continued)

Measures

- **Refrigeration**
  - Anti-sweat heater controls
  - Free cooling by direct use of outdoor air
  - Auto closer for freezers and coolers
  - Curtains
  - Gaskets
  - Evaporator fan controllers
  - Electronically commutated motors

8. Commercial and Industrial – Small Business Direct Install (continued)

- **Lighting**
  - Upgrade T12 fluorescent lamps and older technology ballasts to High Performance and low wattage T8 lamps and ballasts
    - replacement of old fixtures where appropriate
  - replacement of High Intensity Discharge (HID) fixtures with High Performance T8 or T5 fixtures
  - replacement of incandescent exit signs with LED exit signs
  - CFL retrofits
  - installation of occupancy sensor lighting controls
- **Programmable thermostats**
- May address **HVAC**

8. Commercial and Industrial – Small Business Direct Install (continued)

Strategies

- May authorize implementation contractor to work with third parties (local business associations or Chambers of Commerce) to further advance program participation
- May provide targeted marketing support and either approves or develops all program marketing materials

8. Commercial and Industrial – Small Business Direct Install (continued)

- Level of incentives determined by ENSC, currently 80% of overall project cost
- Incentive paid directly to implementation contractor to minimize out-of-pocket expenses
- ENSC offers financing to cover balance of customer costs
- Depending on development of other programs, to balance costs and savings of overall portfolio, or achieve objectives of DSM Plan within established budget, ENSC may vary
  - outreach and marketing strategies
  - project eligibility thresholds
  - other program design features to increase opportunities for participation

Preliminary Budget / Energy Savings Projections

2012 DSM Plan	Budget ($M 2011)	Incremental Annual Net Energy Savings at Generator (GWh)
ENSC PROGRAMS		
Residential		
Efficient Products	3.45	13.8
Existing Houses	8.94	13.2
Low Income Households	5.29	5.3
New Houses	4.30	5.7
Home Energy Report	1.90	38.3
Commercial & Industrial		
Prescriptive	6.48	25.1
Custom	14.37	56.0
Small Business Direct Install	6.37	18.2
Enabling Strategies		
Education and Outreach	2.00	-
Development and Research	1.50	-
Other Enabling Strategies	1.50	-
OTHER		
Codes & Standards	-	10.0
Overachievements from 2008-09 DSM programs	-	19.5
TOTAL	**56.10**	**205.0**

Discussion

Residential

1. Efficient Products
2. Existing Houses (includes fuel substitution, pilot in 2011)
3. Low Income Households (includes fuel substitution, pilot in 2011)
4. New Houses
5. Home Energy Report (new in 2012)

Commercial and Industrial

6. Prescriptive Rebate for Retrofit and New Construction (also includes Smart Lighting Choices)
7. Custom for Retrofit and New Construction (also includes fuel substitution, new in 2012)
8. Small Business Direct Install

Preliminary Budget / Energy Savings Projections

NON-CONFIDENTIAL

Request IR-23:

Does ENSC consider the preliminary budget / energy savings projections on slide 51 of the above mentioned presentation to have been a realistic estimate of achievable energy savings for 2012 at the time? For each program? Why?

Response IR-23:

Yes, ENSC considered the preliminary budget/energy savings projections on slide 51 to be a realistic estimate at the time for each program.

At the time of the above mentioned presentation:

- Savings from projects by the Extra-Large Industrials were not known to ENSC. Therefore, the total projected energy savings for all programs were higher than those in the filed 2012 DSM Plan

- The preliminary, projected energy savings for the Home Energy Report program assumed a very aggressive program rollout with a pilot program initiated early in 2011

- The preliminary, projected energy savings for the Existing Houses and Low Income Households programs reflected an aggressive target for fuel substitution activity that was higher than in the 2012 DSM Plan

The preliminary, projected energy savings from the following programs: Efficient Products, New Houses, Prescriptive, Custom and Small Business Direct Install were considered realistic estimates in terms of program costs per energy savings, based on the program budgets and ENSC's data for Nova Scotia or similar programs elsewhere.

NON-CONFIDENTIAL

Request IR-24:

In the event that the ELI savings were not available, would ENSC seek savings in other program areas? For each of the following: Efficient Products? Existing Houses? Low-Income Households? New Houses? Home Energy Report? C&I Prescriptive? C&I Custom? Small Business Direct Install? Would any savings over and above the filed plan be achievable in each of these programs in 2012, for each program? What level of savings would ENSC consider to be achievable, for each program?

Response IR-24:

Please refer to EAC IR-22, Attachment 1, Slide 51.

NON-CONFIDENTIAL

Request IR-25:

Please explain if ENSC views the IRP as a prescriptive document or as a reference point on which to base its DSM decisions regarding ENSC budgets and energy savings targets.

Response IR-25:

Please refer to Avon IR-1a.

NON-CONFIDENTIAL

Request IR-26:

Please produce from the IRP 2007, Appendix F.

Response IR-26:

Please refer to Attachment 1.

2009 IRP UPDATE
Responses to Stakeholder Input on Basic Assumptions
June 11, 2009

Introduction

On May 7, 2009, NSPI issued the initial draft of 2009 IRP Update Basic Assumptions which had been developed by NSPI jointly with Board staff and consultants (the "Working Group"), to IRP participants.

On May 14, 2009, NSPI facilitated a Technical Conference for participants at which the basic assumptions and plan themes contained in the May 7, 2009 initial draft were presented by NSPI and with support from members of the Working Group. Participants were provided an opportunity to comment and ask questions on the assumptions and plan themes.

Following the Technical Conference, on May 21, 2009, IRP participants submitted written comment for consideration with respect to the assumptions and plan themes. Comments were received from:

1. Alton Gas
2. The Avon Group
3. Ecology Action Centre
4. Minas Basin
5. NewPage Bowater
6. NS Department of Environment/NS Department of Energy

NSPI and the Working Group have reviewed and considered all input received and as a result NSPI has made several changes to the assumptions which will be modeled in the IRP update. NSPI has paraphrased the question or comment and provided a response in the summary table below.

Context for Responses

To provide context for some of the responses below, it may be helpful to provide additional insight into how the model works.

Strategist is a long term generation planning tool and as such uses load duration curves and probabilistic techniques to dispatch thermal units in order to reduce processing time when optimizing expansion plans. Operational issues such as load following, maintaining operational reserves, and tie line load control require an hourly dispatch model. This level of detail is not appropriate for directional long term planning purposes, and is not incorporated in the Strategist model. The IRP analysis will be reviewed with these types of synergies in mind and as appropriate, comments will be made in the Final Report, but the model will not optimize for them. Within the IRP context therefore:

a) Conclusions about storage and load following economics will not be made.

b) The back-up adder for wind will act as a placeholder for such costs in the IRP to acknowledge economically that there will be a cost to follow wind.

c) There will not be dynamic or hourly detailed load following modeling performed in the IRP to compare the detailed economics of buying load following services on the NS-NB tie, via back-up (capacity) adder, CAES (Compressed Air Energy Storage), or other specific projects that could support wind.

d) The CAES option will be evaluated on its ability to mitigate CO_2 and as a dispatchable resource.

e) If an enabling project such as import/second tie to New Brunswick (for example, if part of a large non-emitting PPA resource) or gas generation is selected in the IRP Preferred Plan due to long term energy economics, robustness, and other factors, NSPI can in the future consider how such a characteristic would also enable load following services/wind integration. The specific justifications and business cases to compare options for their load following capability or other operational/reliability considerations, in terms of specific costs and benefits, would be done outside the scope of the IRP Update.

1	**Stakeholder**	Alton Gas
	Topic	Future Supply Side
	Suggestions/Comments	Use costs for CAES similar to LM 6000.
	Response	We have reviewed the additional information provided by Alton Gas as well as submissions made in 2006. The capital equipment associated with this installation includes: Gas Turbine, Turbo Expander, and Compressors and Caverns plus all related auxiliary equipment. Using Alton's data NSPI has confirmed the capital cost of this equipment for indicative modeling purposes. Further work would be required to vet the engineering details of the Alton project.
2	**Stakeholder**	Alton Gas
	Topic	PPA Renewables
	Suggestions/Comments	Use capacity factor for CAES similar to gas-fired combustion turbine.
	Response	Having reviewed the information provided by Alton Gas, costing appears to reflect an 8-hour storage volume and 77% efficiency, which may be either thermal or recovery efficiency. Eight hours equates to 33% capacity factor and is further reduced to 26% if adjusted for efficiency. Based on 85% reliability, the capacity factor would be adjusted to 22%. If the 77% efficiency is based on thermal, there would be an additional heat rate penalty of a 28% capacity factor. Given that this technology is new, it is NSPI's intention to offer the model a capacity factor of 21% and the $/MWh as referenced on slide 39 of the Basic Assumptions. NSPI will further investigate to better understand the referenced efficiency factor.
3	**Stakeholder**	Avon
	Topic	Plans
	Suggestions/Comments	Consider a scenario where carbon caps are met through trading or offsets.
	Response	A key focus of the 2009 IRP Update versus the 2007 IRP is how to meet reasonable physical carbon reduction, as opposed to a detailed analysis of the pros and cons of meeting CO2 hard caps versus compliance using offsets. The 2009 IRP Update Base Case run will be with CO2

		assumptions set as hard cap targets, as prescribed in the Nova Scotia Climate Change Action Plan (January 2009) and draft regulations (February 2009). In scenario runs with near and long term CO2 targets that are deeper than Base, offsets will be used up to 2020, at the CO2 credit prices outlined in the Basic Assumptions.
4	**Stakeholder**	Avon
	Topic	Plans
	Suggestions/Comments	Provide NPV and include cost analysis over 25 years
	Response	This can be provided with the Analysis/Final Report.
5	**Stakeholder**	Avon
	Topic	Plans
	Suggestions/Comments	Perform sensitivity of impacts of reduction of costs if implementation delayed
	Response	To the extent that technology is pulled into the plans to meet load and emissions constraints, an assessment will be made as to the appropriate sensitivities to perform in order to test the robustness of that technology's call into a plan. The high-low fuel and high-low capital cost assumptions may be selected as possible sensitivities against which NSPI would want to test. In terms of the specific request to test the sensitivity of plans to lower technology costs due to a delay in implementation, this could be thought of as being directionally covered by a low capital cost test.
6	**Stakeholder**	EAC
	Topic	DSM
	Suggestions/Comments	To more fully understand the DSM assumptions, provide an accounting of energy savings and program costs in each year.
	Response	The summary provided in the basic assumptions shows the DSM information at a number of intervals over the 25 year timeline. The additional requested information has been provided in Attachment 1.
7	**Stakeholder**	EAC

	Topic	DSM
	Suggestions/Comments	Resource savings such as water, oil and operations and maintenance are not currently taken into consideration. If the IRP only wishes to optimize with respect to the electric system, then the IRP should use a utility cost test rather than a TRC test which counts all resources.
	Response	When developing the DSM assumptions for the IRP, the analysis did not include such non-electric benefits and costs. This is consistent with the approach used in the 2007 IRP and in NSPI's recent DSM filings. As explained in the basic assumptions, since DSM is a cost-effective option compared to supply alternatives, the model will pick DSM over other alternatives. The suggestion to either enhance the benefits associated with DSM or to use to the utility costs instead of total costs would increase the attractiveness of DSM versus supply options. The DSM as projected will be in the Reference plan and increasing the economic attractiveness of DSM will not change that outcome. The total resource cost of DSM calculated using electric only benefits is appropriate for the IRP Update.
8	**Stakeholder**	EAC
	Topic	Plans
	Suggestions/Comments	Use Kyoto rather than Deep Green.
	Response	NSPI will develop a "Kyoto World" CO2 assumption set and model this world with 2010 - 2020 able to be met via offsets and 2020 onward as physical hard caps. The "Kyoto World" modeled in the 2007 IRP, was: 2010 6.4 Mtonnes 2015 5.6 Mtonnes 2020 4.8 Mtonnes 2025 4.5 Mtonnes 2030 4.1 Mtonnes
9	**Stakeholder**	EAC
	Topic	Future Supply Side
	Suggestions/Comments	Provide justification for CCS cost estimates.
	Response	The carbon capture cost estimates are based on detailed

studies being carried out by the various organizations within CCPC (Canadian Clean Power Coalition) which includes a number of utilities, EPRI (Electric Power Research Institute), Natural Resources Canada and others. NSPI also participates in both the IEA (International Energy Agency) Clean Fossil Fuel Task Group and the IEA Green House Gas Task Group which provides insight into the status of the technology globally.

The Pembina data was reviewed but, as it is several years old (2005), NSPI is comfortable that its cost information as presented for 2009 modeling purposes is appropriate. For clarification regarding the $12 USD per tonne for sequestration, this is specifically for "outside the fence sequestration costs" such as pipeline, well field/reservoir monitoring, etc. This is in addition to the capture capital costs; for example, retrofit to existing plants or inherent in costs of a new CCS plant.

10	**Stakeholder**	EAC
	Topic	Plans
	Suggestions/Comments	Include CCS sensitivity analysis with high/low estimates.
	Response	Upon review of the plans' outputs, it will be determined whether high or low or both sensitivity tests of CCS are warranted. For instance, if a plan calls for CCS, NSPI could run the plan with CCS cost set to its High, and see how the plan's rank order among the others (in terms of cost) changes.
11	**Stakeholder**	EAC
	Topic	Plans
	Suggestions/Comments	Include a "Renewable with energy storage" plan excluding CCS & large-scale interconnection/imports but including aggressive DSM, renewables, transmission upgrades, energy storage and demand control.
	Response	It is possible that from the base runs there will be plans without CCS and large-scale interconnection/imports – that is, with DSM, in-province renewables, some transmission upgrades to enable, etc. - without needing to create a separate scenario. If all plans among the least cost contenders rely on these resources, NSPI could run a

		plan without them and assess. Energy storage can be discussed qualitatively in terms of how it would augment/support wind/DSM/load control but it will not be modeled as an explicit feature of the IRP runs. Please also refer to the Context for Responses in the Introduction.
12	**Stakeholder**	Minas Basin
	Topic	Plans
	Suggestions/Comments	Model different choices for pricing of renewable energy (provided 3 options).
	Response	The purpose of an IRP is to identify the combination of supply and demand alternatives which most effectively meets long-term system load requirements across broad ranges of assumptions and constraints. Renewable resources are modeled within the IRP at the estimated cost to construct or purchase this generation. Renewables are selected for inclusion in the Reference Plan based on the comparison of the cost and attributes of this generation with other demand and supply options. The actual procurement of renewable resources, including the pricing and ownership of this generation, are matters determined when the procurement programs are executed.
13	**Stakeholder**	NPB
	Topic	Fuel
	Suggestions/Comments	Natural Gas Base Case should use NYMEX rather than PIRA.
	Response	Forward strips are not appropriate for long-term forecasting. Long-term supply/demand fundamental models are more appropriate to predict future fuel prices.
14	**Stakeholder**	NPB
	Topic	Fuel
	Suggestions/Comments	May 2009 PIRA is 10% less than Nov 2008. Reassess fuel once June PIRA, Wood MacKenzie and Jacob's updates are available.
	Response	Pricing for all fuels needs to be from a consistent timeframe to ensure consistency in underlying macro-

economic assumptions.

Decreases in prices from November to May are not material in the long-term perspective of the IRP. If the June reports show significant change, NSPI will review. For instance, the range (for example, low) to be used in sensitivity tests could be widened if appropriate.

15	**Stakeholder**	NPB
	Topic	Future Supply Side
	Suggestions/Comments	Use +30/-30% for capital costs except where current pricing available.
	Response	Upon reviewing cost assumptions for the large future additions in outer years, a -20% is to be used in most cases. Given that owner's costs were not included in NPB's numbers and this would account for approximately an additional 10%, NSPI is in the -30% range suggested. NSPI will, however, adjust the IGCC with capture, changing the low estimate from 2,608 to 2,282, since the Base value is relatively conservative. The other estimates have been reviewed and, using the known contract value for the PC 400MW as an anchor along with NSPI's own builds, they are considered reasonable for modeling purposes.
16	**Stakeholder**	NPB
	Topic	PPA – Renewables
	Suggestions/Comments	Use 28-30% for on-shore wind and reduce off-shore wind from 38%.
	Response	NSPI is satisfied that the on-shore wind capacity factor of 32% and the off-shore capacity factor of 38% are reasonable for use as indicative capacity factors for long-term planning purposes. For on-shore wind, it is supported by the actual performance of existing IPP projects as well as the use of 32% as the indicative capacity factor for wind in the Wholesale Tariffs recently approved by the Board.
17	**Stakeholder**	NPB
	Topic	Future Supply Side
	Suggestions/Comments	Clarify if effects of new technology capital additions on unit performance and energy replacement during retrofit

		are included in the model.
	Response	The Strategist model includes shutdown times for all units. Major capital additions are designed around installing equipment during a planned shutdown window. An example is the Trenton 5 Baghouse which will be linked into the planned shutdown period. This approach would be used for all the additions contemplated. Should additional considerations be identified, they would be addressed at the time a work order was advanced. New technology options do include material parasitic power penalties in terms of net output reductions, so the effect of recurring annual replacement energy due to parasitic power is captured in the model (for example, FGD, CCS, etc.).
18	**Stakeholder**	NPB
	Topic	Future Supply Side
	Suggestions/Comments	In the final report, make reference to capital costs for plants with nascent technology such as carbon capture are speculative, and construction of "first of kind" plants in near term is premised on significant capital costs.
	Response	NSPI costs on carbon capture study plants are based on advanced engineering studies that are projecting plants to be built in the 2015 time frame in other jurisdictions. These plants are all hoped to be part of the “20/20” solution advanced by the G8 developed economies – that is, an expressed desire to have 20 fully up and running carbon capture plants by the year 2020. At this level they would then be seen as fully commercial solutions. NSPI can discuss in the Final Report.
19	**Stakeholder**	NPB
	Topic	DSM
	Suggestions/Comments	Did not reduce DSM projection when Pulp & Paper removed.
	Response	This is correct. When NPB requested the DSM projection for Pulp & Paper be removed from the 2007 IRP projection, the energy saving was assumed to come from other classes within the Commercial & Industrial sector, which kept the 8-year achievable energy potential for those sectors at 23%. This level of achievable

potential is realistic.

20	**Stakeholder**	NPB
	Topic	DSM
	Suggestions/Comments	The modeling should not be locked in, but should allow for varying degrees of DSM effectiveness, which would allow for DSM to be available to be picked. An IRP conducted in this fashion provides little assistance in determining how much to actually spend on DSM in future, since such a determination would require an assessment of the achievable DSM and whether the benefits can be achieved for the costs assumed in the IRP.
	Response	The Basic Assumptions have noted that "DSM is a relatively cost effective option compared to supply side alternatives". Current estimates are that DSM costs would have to be significantly higher than projected in order to be displaced by a supply side option. While it will not be "locked in", as much DSM as is profiled will be included in the plans selected. The question with respect to DSM is not one of modeling, but rather one of achievability. A level of two percent annual energy savings will position Nova Scotia as a leader in DSM. This amount of energy savings is in line with other leading North American jurisdictions. (Other potential leaders include Illinois, Ohio, New York, Maryland and Vermont). The economic potential identified in the eight-year potential study is reached before Year 20 of the plan. Electric DSM programs in Nova Scotia are at an early stage. In the future, and at an appropriate time, a new potential study will be completed. This will incorporate the learning and experience since the 2006 DSM Potential Study and will produce a new projection of DSM potential and costs for use in a future IRP. As noted in the Technical Conference and in EAC's comments in this IRP Update, there is no consensus as to whether DSM costs will actually go up or down as programs expand: - As noted in Response #6, providing a lower cost stream associated with DSM is not expected to change the Reference plan. - Should DSM costs be significantly more expensive than

projected, it is plausible that a supply side option would be chosen in lieu.

A Higher Load World can approximate the scenario where DSM costs are significantly higher or where achievable amounts are lower. In a Higher Load World, additional supply side options are expected to be required versus the Base Load run in order to meet the higher demand requirement while maintaining environmental constraints.

The output of a High Load World will be important to consider and understand in developing the Reference or Preferred plan and the 2009 IRP Final Report's Recommendations.

21	**Stakeholder**	NPB
	Topic	DSM
	Suggestions/Comments	"This profile is ambitious, one which would position Nova Scotia as a leader in energy conservation". This statement appears to be making a policy decision at the assumption level.
	Response	This is a policy decision, one that has been made based on insight from the 2007 IRP and with direction articulated in the NS Government's Energy Strategy: "This strategy lays a path for Nova Scotia… to become a leader in energy efficiency and conservation" (page 34) "After conservation and efficiency, renewable energy is Nova Scotia's best opportunity to meet our energy goals" (page 15) "This strategy makes a series of choices about how to deploy our limited resources. It begins with those that offer the greatest immediate impact: energy conservation and efficiency" (page 34) This statement is further supplemented by Nova Scotia's announced draft GHG regulations concerning hard caps and reductions. Successful DSM will be important in reaching the contemplated GHG hard cap targets.
22	**Stakeholder**	NPB
	Topic	DSM
	Suggestions/Comments	All DSM is assumed to be included in the projection used in the IRP. If no money is spent on customer-funded DSM programs, this form of DSM will still occur. It is unclear how customer costs will be

		appropriately modeled.
	Response	The IRP includes a projection of DSM achievable potential which is not reflected in the load forecast and can be attained through a variety of means including: -incentives through electric DSM programs -projects completely initiated and paid for by the customer -projects activated by electric utilities -mandates by government standards -incentives by government programs -various market forces In a potential DSM study, it is not possible to know how or when these various energy conservation alternatives will occur. Assumptions are made in the study which affect the estimates of utility and customer costs. As noted in the comment, some of this potential DSM may still occur without electric DSM programs. If so, this would simply change who pays the costs (whether the utility or the customer). For instance, if a standard is introduced, the costs which may have once been partially or wholly paid for under DSM programs may become entirely customer costs. Such changes do not affect the DSM economics or costs used in the IRP (total cost = customer + utility costs).
23	**Stakeholder**	NPB
	Topic	Transmission
	Suggestions/Comments	Provide more information about transmission costs.
	Response	The Standards of Conduct restrict the level of detail that can be provided. Qualitatively, network upgrade capital costs were developed by: - Preparing independent high-level feasibility assessments for each option - Using wind resource locations where wind resource options covered large geographic areas, such as mainland Nova Scotia - Assigning lowest identified network upgrade costs to the first block and so on for all blocks - Assuming Capacity Network Service for each resource option: o Network upgrades were based on the ability to deliver the full capacity of each option independently. Some transmission upgrades

may be common to more than one option as shown in the Common Facilities Table on slide 62 of the Basic Assumptions.

  - o Generation Interconnection Procedures (GIP) provide for interconnection applications for 'energy' service instead of capacity service. However, output capacity can be curtailed with this option.

- Assuming current resource economic dispatch patterns for each option:
  - o Flows on interfaces depend on the generation running to serve the load. As new generation resources were added, the highest cost generator, based on current economic dispatch, was curtailed. Changing the generator dispatch pattern away from the current economic model would affect the flows on interfaces and potentially the required network upgrades.

24	**Stakeholder**	NPB
	Topic	Load Forecast
	Suggestions/Comments	Bookend Base Case at a level between proposed low and base.
	Response	NSPI does not intend to have a Lower Load World run in the 2009 IRP Update. To the extent that this World is less likely to be the future direction, the priorities of the 2009 IRP Update are focussed on other key interest areas. A Lower Load optimization would provide a picture of the resources which may be required if inherent Load is lower; for example, fewer supply-side resources to meet energy demands than the Base or High Load case. Instead, the focus will be on meeting energy and environmental needs if Load is higher than anticipated for whatever reason.
25	**Stakeholder**	NPB
	Topic	PPA – Renewables
	Suggestions/Comments	What is the difference in assumed price for wind energy - XXX vs XXX?
	Response	The prices are different to represent thinking that over

time the cost of wind will change.

26	**Stakeholder**	NPB
	Topic	PPA – Renewables
	Suggestions/Comments	How were off-shore wind, tidal and CAES prices derived?
	Response	These costs are based on a combination of indicative capital and O&M estimates, estimated capacity factors/performance, and NSPI's judgment in general as to how the pricing of each technology will develop over the next several years. The prices are indicative and considered suitable for directional, long term modeling purposes.
27	**Stakeholder**	NSDOE
	Topic	Emissions
	Suggestions/Comments	Lower CO2 base case for 2030 to 5.5M tonnes (difference between low and high).
	Response	The Federal Government has referred to a reduction of up to 65% from current levels by 2040 to 2050. Based on recent policy announcements by the US and discussions of harmonization of Canadian and US regulations, NSPI believes that a 65% reduction target is appropriate. A 65% reduction of 10Mt in 2045 would result in a Base target of 3.5Mt. Given a straight line trajectory from the 2020 Base target of 7.5Mt, to a 2045 Base target of 3.5Mt, the 2030 Base target would be 5.9Mt. As a result, we will revise the assumption to reflect a 2030 Base target of 5.9Mt.
28	**Stakeholder**	NSDOE
	Topic	Emissions
	Suggestions/Comments	Provide the number of offsets required to meet 8.6 in 2010 high case.
	Response	The base case calls for 9.7 million tonnes in 2010 with real reductions. A target instead of 8.6 would require 1.1 million tonnes to be offset.
29	**Stakeholder**	NSDOE

	Topic	Emissions
	Suggestions/Comments	Provide NatSource (Source of $/tonne offsets).
	Response	A copy has been provided to all stakeholders.
30	**Stakeholder**	NSDOE
	Topic	Emissions
	Suggestions/Comments	Reduce SO2 2015 high case to meet the Federal Government's proposed level (18,000 tonnes).
	Response	The 2020 target of 36,200 tonnes represents a significant reduction, likely beyond co-benefits of GHG abatement. The 2015 target represents a calculated middle ground.
31	**Stakeholder**	NSDOE
	Topic	Emissions
	Suggestions/Comments	25% of renewables by 2020 doesn't net out for DSM.
	Response	Adding pre-2001 renewables of 8.5% + 14% RES 2019, to get 22.5%, does not factor in the effect of forecast energy sales net of the DSM effect. With the effect of DSM included, the RES level at 2020 would be approximately 25% and hence the RES as proposed would achieve the goal of 25% in 2020. NSPI will continue to assess the level of renewables it must pursue to be comfortable that RES and other environmental requirements are able to be met.
32	**Stakeholder**	NSDOE
	Topic	Future Supply Side
	Suggestions/Comments	Capital costs should be based on typical years rather than focusing on a single year (ie. 2008 $Cdn).
	Response	2008 dollars/overnight indicative costs are used for the purpose of modeling, and escalation factors are built into the model. The research to derive the estimates is not just based on snapshot 2008 project costs but rather several recent years' studies. For modeling purposes 2008$ is the starting point and then escalation factors are applied to ensure economics and NPVs are on consistent terms.

33	**Stakeholder**	NSDOE
	Topic	Future Supply Side
	Suggestions/Comments	In comparing IGCC 400 (with and without CO2 capture), the Base delta of 1407M differs from the PC 400 delta (with and without capture) of 620M. Are the deltas correct and, if so, why the difference?
	Response	The deltas are correct. The difference, in part, is due to the advancement of gas turbine technology for the combustion of syngas ("synthetic gas", resulting from gasification process) versus a standard unit. As work is advanced on integration to increase reliability and system efficiency, prices have increased and are reflected in the costing. In the case of the PC unit, the addition of post combustion capture technology would be considered "bolt-on" and thus less capital intensive.
34	**Stakeholder**	NSDOE
	Topic	PPA - Renewables
	Suggestions/Comments	Give consideration to particulate emissions.
	Response	Particulate emissions are being addressed in NSPI's planned test program for biomass firing with the intent to develop a fuel and combustion technology that meets or improves upon all regulatory requirements.
35	**Stakeholder**	NSDOE
	Topic	PPA - Renewables
	Suggestions/Comments	27% moisture content is too high for biomass.
	Response	This number is derived from the actual "as fired" sample used at Point Aconi when NSPI burned a small amount of processed (size reduced) wood chips. Raw wood chips would be expected to have higher moisture content and wood pellets lower moisture content.
36	**Stakeholder**	NSDOE
	Topic	PPA – Renewables
	Suggestions/Comments	Use series of smaller blocks for biomass.
	Response	NSPI will offer the model another small block of biomass, ~15 MW or ~100 GWh, at the capacity factor and PPA price noted on slide 39 of the Basic Assumptions. The

sizing is generic and not intended to pre-judge a maximum or minimum amount of biomass potentially of interest in the future. Given the other Biomass alternatives being considered in the model for the 2009 IRP Update, this level in addition to the options already presented is thought to be sufficient to test the directional economics of Biomass PPA options. The specific justification or business case details of any project would be tested at the time of application or submission within an RFP process.

37	**Stakeholder**	NSDOE
	Topic	PPA – Renewables
	Suggestions/Comments	Tidal capacity factor of 18% is too low.
	Response	NSPI is using a conservative figure as tidal energy is an emerging technology with expectations not yet well understood. NSPI will revise the number to reflect a capacity factor of 20% which has been provided by the Technology Provider, Open Hydro.
38	**Stakeholder**	NSDOE
	Topic	Load Forecast
	Suggestions/Comments	Why is there an increase in energy requirement in March?
	Response	Even though March may be a warmer month, the additional 2-3 days in March (vs. February) can result in an increased energy requirement.
39	**Stakeholder**	NSDOE
	Topic	DSM
	Suggestions/Comments	The utility costs jump from \$23M in 2010 to \$82M in 2013, and total costs jump from \$38M in 2010 to \$142M in 2013. Are these correct? - the 2007 IRP estimated \$50M annually.
	Response	The costs are correct; the profile for this IRP update is the high case from 2007 and adjusted with current information. The first 5 years (2008-2013) reflect the energy savings and costs shown in NSPI's 2010 DSM filing. Time value of money adjustments were also made to put costs in the right terms (the 2007 IRP data was in 2006 dollars)

40	**Stakeholder**	NSDOE
	Topic	DSM
	Suggestions/Comments	Include Smart Grid Technology.
	Response	The IRP will not explicitly model this technology. The IRP contains a DSM roadmap that can be met through a variety of technologies and programs and does not preclude any.
41	**Stakeholder**	NSDOE
	Topic	Plans
	Suggestions/Comments	Integrate highly constrained CO2 and pollutants by optimizing Deep Green run on C02 first, then fix C02 and optimize air pollutants
	Response	In the Deep Green (Kyoto) run NSPI will optimize CO2 to its Kyoto settings and the other air emissions to their Base and then assess for co-benefits of the deeper CO2 track with the other air emissions. (While possible to do as suggested, the intention of the Kyoto World has been to isolate CO2 as the more strict factor to assess how the supply side must react to comply; and as such what the co-benefits with the other emissions would look like – for example, such that SO2 or NOx or Hg removal technologies would not be advanced ahead of what a Kyoto track could take each to a few years later, for instance 2015 versus 2020 timing.)

2009 IRP Update

Response to Stakeholder Comments on Analysis Results

Introduction

On September 22, 2009, NSPI issued the Analysis Results to stakeholders. On September 30, NSPI facilitated a Technical Conference for participants at which the Analysis Results were presented. Participants were provided an opportunity to comment and ask questions on the Analysis Results, and were given an opportunity to submit written comments for consideration. On October 13, 2009, comments were received from the Departments of Energy and Environment.

NSPI has paraphrased the questions and comments and provided responses in the table below.

1	**Stakeholder**	Departments of Energy and Environment
	Suggestions/Comments	If biomass is selected for future electricity generation, it should be subject to testing and verification of outcomes, with approval by government.
	Response	Agreed. NSPI will engage Department of Energy and Department of Environment to ensure appropriate test programs are established for verification of continued compliance to operating permit(s) for co-fired unit(s)
2	**Stakeholder**	Departments of Energy and Environment
	Suggestions/Comments	Would a large PPA of 300 MW be large hydro, nuclear or tidal?
	Response	The Basic Assumptions identified the large non emitting PPA contemplated in the 2009 IRP Update analysis to be out of province hydro. However, it could be from any non-emitting resource.
3	**Stakeholder**	Departments of Energy and Environment
	Suggestions/Comments	The required lead time for a large PPA such as nuclear, large hydro or tidal would be 5-10 years.
	Response	Agreed.

2009 IRP UPDATE
Responses to Stakeholder Input on draft IRP Update Report
November 30, 2009

Introduction

On October 29, 2009, NSPI issued the draft 2009 IRP Update Report which had been developed by NSPI jointly with Board staff and consultants (the Working Group), to IRP participants. Participants were given the opportunity to submit written comment for consideration in the final Report. Comments were received from:

1. Nova Scotia Department of Environment
2. New Page Port Hawkesbury Corp. and Bowater Mersey Paper Company Ltd. (NPB)

NSPI and the Working Group have reviewed and considered all input received and as a result NSPI has made several changes to the report. NSPI has paraphrased the question or comment and provided a response in the summary table below.

1	**Stakeholder**	Nova Scotia Department of Environment
	Topic	Biomass co-firing
	Suggestions/Comments	Relative to the fourth bullet on page 36, it should be anticipated that biomass co-firing testing processes may extend beyond "verification of continued compliance with operating permit(s) for co-fired unit(s)" to identifying new technical and emission issues and options not existing currently in operating approvals.
	Response	NSPI acknowledges this point.
2	**Stakeholder**	NPB
	Topic	Appendix B: Board Staff & Consultants Statement
	Suggestions/Comments	It would be important information for interested parties if the Board staff and consultants have different views than NSPI with respect to the IRP Update results. The final

		comments should be provided to interested parties well in advance of the issuance of the Final Report, so that interested parties can have the benefit of those views and provide further comments on the Draft IPR Update if warranted.
	Response	The final comments of Board staff and consultants were sent to stakeholders on November 24.
3	**Stakeholder**	NPB
	Topic	Action Plan
	Suggestions/Comments	Add second bullet on page 34 under the Action Plan heading "continue to Develop the Resources Identified in the 2009 IRP Update Plan Pre-2013", which would read as follows: "Monitor the impact of DSM to determine whether the assumed energy savings levels are being achieved. Provide annual reports to the Board and staff and interested parties on the energy savings level achieved by DSM in the prior 12-month period."
	Response	NSPI agrees with this statement. This action will be addressed as part of DSM Evaluation, Verification and Measurement processes.
4	**Stakeholder**	NPB
	Topic	Action Plan
	Suggestions/Comments	Add another bulleted item to the list of bullets in Part I of the Action Plan which starts on page 34 as follows: "Provide an updated load forecast to Board staff and interested parties on an annual basis."
	Response	NSPI provides a 10 Year System Outlook (updated annually), an 18 Month Forecast (weekly data updated in April and October) and a 10 Year Load and Resource Assessment (monthly data updated annually) and these documents are available publicly at: http://oasis.nspower.ca/en/home/oasis/forecastsandassessments.aspx

5	**Stakeholder**	NPB
	Topic	Action Plan
	Suggestions/Comments	Add the following words at the end of the final bullet on page 36 that references the exploring of implications of continued low natural gas prices for preferred resource plans: ", and monitor the behaviour of natural gas prices in relation to the values of other parameters and provide an annual report in this regard to the Board and interested parties."
	Response	NSPI provides forecasts containing updated price strips that are available on an ongoing basis in the FAM Confidential Data Room. NSPI has also added the following additional bullet to the Action Plan at page 38 which confirms that the annual progress reports will report on each action item individually: "These progress reports will address each of the bulleted items listed in Parts I and II individually, describing what has been accomplished since the last report and cumulatively since the 2009 IRP Update. Looking ahead, they will indicate next steps to be undertaken and the associated timeline where applicable."
6	**Stakeholder**	NPB
	Topic	Action Plan
	Suggestions/Comments	In the last paragraph on page 32 relative to regular progress reports, insert the words "and interested parties" after the word "Board" in the two places where the word "Board" occurs in that paragraph.
	Response	Agreed. NSPI has incorporated these changes in the Final Report.
7	**Stakeholder**	NPB
	Topic	Action Plan
	Suggestions/Comments	In the first bullet on page 35 relative to the establishment of a collaborative DSM working group to support transition to a new Administrator, add the words "and representatives of each of the industrial, residential and municipal customer classes" after the word "consultants".

	Response	Pursuant to section 40, of the Efficiency Nova Scotia Act, Bill 49, 1st Sess., 61st General Assembly, NS 2009 (assented to 5 November 2009, c. 3), NSPI and the Administrator are required to enter into a transition plan which pursuant to section 42 must be approved by the UARB. It is appropriate that the collaboration contemplated by the first bullet on page 35 be the parties who will be involved in the process of transition of the functional responsibilities associated with DSM administration.
8	**Stakeholder**	NPB
	Topic	Action Plan
	Suggestions/Comments	In the second and third last bullets on page 35 relative to transmission (providing a confidential technical briefing and engaging Board staff in advance of significant transmission-related capital applications), add the words "and interested parties" after the word "Board Staff".
	Response	With respect to the third last bullet, as required by the Market Rules, NSPI annually files a 10 Year System Outlook which contains transmission planning information. It is available on the following site: http://oasis.nspower.ca/en/home/oasis/forecastsandassessments.aspx. The briefing included in the Action Plan is intended to be an informal discussion between NSPI and the Board about confidential transmission infrastructure issues and emerging industry developments. With respect to the second last bullet, Technical Conferences will be held to share information about significant transmission-related capital applications.
9	**Stakeholder**	NPB
	Topic	Action Plan
	Suggestions/Comments	In the first bullet on page 38 relative to the annual progress report, add the words "and interested parties" after the word "Board" in each of the two places in which it occurs.
	Response	Agreed. NSPI has incorporated these changes in the Final Report.

10	**Stakeholder**	NPB
	Topic	Action Plan
	Suggestions/Comments	In the final bullet on page 38 relative to consideration for an updated IRP in 2012, add the words "in conjunction with Board staff and interested parties" after the word "consider".
	Response	Agreed. NSPI has incorporated these changes in the Final Report.

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Request IR-27:

Low-cost Programs: Program costs will be minimized, where doing so does not hinder meeting overall IRP targets in both the short and long term.

Long-term success: In planning DSM initiatives, it is important to achieve specific savings targets and to build capacity for the long-term success of DSM efforts, including market transformation. (p.21)

Efficiency Nova Scotia is focused on building capacity to enable Nova Scotia to become a leader in energy-efficiency services, innovation and know-how. (p.23)

With respect to ENSC's guiding principles, please identify if and how the 2012 DSM Plan will 'not hinder meeting the overall IRP targets in the short and long term' and, as well, how it will 'achieve specific savings targets and build capacity for the long term success of DSM efforts' in light of the unexpected energy savings from ELI and differences in the 2012 DSM budget from what was allocated in the IRP.

Response IR-27:

The 2012 DSM Plan, including the energy savings from ELI, is designed to meet the GWh and MW targets of the IRP. Please refer to EAC IR-5 and Avon IR-1.

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Request IR-28:

Renewable Heating: ENSC will work with governments to support the development of a renewable heating strategy, tapping into the province's substantial renewable heating opportunities. (p.28)

Please describe how ENSC anticipates the development of a renewable heating strategy and how this relates to the transfer of solar hot water and solar air programs from Conserve NS.

Response IR-28:

ENSC has not yet developed its renewable heating strategy. ENSC has recently hired staff responsible for solar and expects to include passive and active solar heat in the renewable heating strategy.

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Request IR-29:

Please provide information with regards to how this strategy will be funded.

Response IR-29:

ENSC will fund its renewable heating strategy primarily through the "Other Enabling Strategies" component of the 2012 DSM Plan. ENSC is also currently in discussions with the provincial government for funding to promote non-electric energy savings, a portion of which may be directed to this strategy.

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Request IR-30:

ENSC's initiatives on fuel substitution will be accompanied by an equally strong emphasis on the importance of sustainability in biomass harvesting and use. (p.32)

Please explain what sustainability benchmarks ENSC is utilizing in its biomass pilot project.

Response IR-30:

ENSC's fuel substitution pilot is still in development. However, ENSC anticipates promoting certified wood pellets and will be engaging in discussions with domestic pellet producers who currently seek sustainable harvesting certification of their pellet production, per expectations from their European customers.

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Request IR-31A:

Please explain if and how ENSC's utilization of biomass in a pilot project relates to provincial government policy initiatives such as the Natural Resources Strategy and other planned utilization of biomass in the province (i.e. Renewable Electricity Plan).

Response IR-31A:

The Renewable Electricity Plan centers on electricity generation using renewables in general, including the use of biomass, specifically. The focus is on large scale generation, not use of renewables at the single-family home or small business scale. In the fuel substitution pilot project for 2011 and the Renewable Heating strategy proposed for 2012, biomass will be used as an end-use fuel for direct space heating. The 2011 pilot program is limited to residential applications, where wood pellets or cord wood have common use. Expansion to commercial or institutional applications adds wood chips as a potential fuel source.

End use of biomass for space heating shares certain objectives with the Renewable Electricity Plan, including: job creation, local economic development, stable energy prices, greenhouse gas reductions and reliance on a Nova Scotian resource. End use of biomass for space heating has the added advantage of relatively high overall efficiency when compared to biomass use for electricity generation.

The use of biomass as a substitute for electricity will emphasize the sustainability of the biomass supply as well as the sustainability of its use (attention to air emissions and impact on air quality).

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Request IR-31B:

ENSC is discussing a mandate for DSM programs for other fuel types with the Nova Scotia Department of Energy. At the time of filing, the timeline, form and oversight mechanism for this mandate had not been finalized. ENSC recognizes the importance of harmonizing DSM programs for electricity and other fuels as much as possible to minimize duplication and administrative costs, and expects this to be reflected in an eventual mandate. In 2011 and 2012, the oversight of energy efficiency and conservation for other fuels is expected to be through the terms and conditions of ENSC's contract with the provincial government. (p.30)

Please provide an update with regards to the status of ENSC's negotiations with government with respect to managing other fuels as a part of its mandate.

Response IR-31B:

ENSC had no responsibility related to other fuels in 2010.

Within the first quarter of 2011, ENSC has taken over operational responsibility for the following provincially-funded energy efficiency programs for other fuels: low-income home energy-efficiency upgrade program, solar program, EnerGuide for existing houses program, EnerInfo energy efficiency enquiry/advisory service and ice-rink energy-efficiency upgrade program. Government continues to own and manage these programs.

Negotiations are in progress for ENSC to administer, beginning in April 2011, a suite of energy efficiency and conservation programs funded by Government under a multi-year contract. Government oversight of these programs will be dictated through the terms and conditions of the contract.

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Request IR-32:

Please provide further details with regards to how this could affect the DSM 2012 plan, including allocation of resources for non-electric fuel substitution programs costs.

Response IR-32:

ENSC management of non-electric energy efficiency programs will have no direct effect on the 2012 DSM Plan or programs. ENSC will keep funds for electricity related programs segregated from funds for other fuels. The cost of program activities for electricity and other fuels will be accounted for separately.

Where circumstances permit, Nova Scotians will be offered one program by ENSC, irrespective of energy source, for example, Existing Houses. From the participant's perspective, any ENSC attention to energy source will be invisible.

Fuel substitution has been designed for the electricity DSM Administrator to substitute in 2011 other energy sources to displace electricity in the residential sector at the pilot scale, and to expand fuel substitution in 2012 as a program for the residential, commercial and industrial sectors.

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Request IR-33:

The creation of ENSC flows from the recommendations of a stakeholder consultation process facilitated by Dr. David Wheeler.17 The final report resulting from this process envisioned a performance-driven oversight mechanism, whereby ENSC would be responsible for delivering a specified amount of energy and demand savings for a specified investment within a defined performance period. Such a mechanism would eventually use a multi-year framework to increase flexibility and, conceivably, reduce the administrative burden of annual regulatory filings. This multi-year framework is similar to approaches used successfully in other jurisdictions, such as Vermont. (p.29)

Please provide further details with regards to the process ENSC would pursue to initiate a performance based approach and a multi-year framework.

Response IR-33:

Please refer to Multeese IR-14.

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Request IR-34:

Please provide further details with respect how performance based approaches and multi-year frameworks function in other jurisdictions, such as Vermont.

Response IR-34:

Performance-based approaches can function in a variety of different ways, but generally share a common thread: a clear set of goals (often multi-year), incentives for achievements and overachievements, and an established process for measuring success.

Vermont's current approach involves three-year periods and a variety of performance metrics (including eight indicators related to electricity savings, one indicator related to non-electric fuel savings and five minimum performance thresholds). In Massachusetts, electric and gas utilities are provided with performance-based incentives that revolve primarily around two indicators (gross economic savings and net lifetime economic savings), as well as minimum performance thresholds.

Please refer to CA IR-35.

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Request IR-35:

Existing Houses: For weatherization and insulation upgrade measures, the program targets electrically heated homes. Policies and procedures will be modified for 2012 to include multi-family buildings and rental housing. (p.8 or 43)

Please indicate whether ENSC would consider extending weatherization services to all homeowners, if given a multi-fuels mandate.

Response IR-35:

Please refer to EAC IR-31B.

ENSC is already providing an operational service to the provincial government for its EnerGuide for Existing Houses program. This program includes incentives for weatherization components, such as caulking and air sealing, basement insulation, wall insulation, attic insulation, windows and doors, etc.

ENSC expects that its multi-year contract with the provincial government will include a program for energy efficiency upgrades to existing homes that maintains a focus on weatherization measures.

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Request IR-36:

New Houses: Each year, approximately 3,000 new houses are built in Nova Scotia, creating new demand for electricity. Many builders and consumers choose electric space heating in residential new construction; this market represents an important, time-sensitive opportunity to secure electrical energy savings. (p.13 of 43)

Please indicate what strategic direction and timeline ENSC foresees in working with government to implement electric home heating codes and standards in new houses to cost-effectively reduce electricity demand and increase efficiency in new homes through codes and standards for electric home heating (4.4).

Response IR-36:

ENSC participates in the Canadian Advisory Council on Energy Efficiency (CACEE) steering committee on Performance Energy Efficiency and Renewables (SCOPEER) and the SCOPEER Resource Task Force (SRTF). These three groups comprise federal and provincial regulators, utilities, standards organizations and manufacturer and consumer representatives, setting the priorities for standards development in Canada. It is these energy efficiency standards that are referenced when setting regulations in Nova Scotia. Before new regulations are adopted, the standard to be referenced must reflect the latest technology, be coordinated across jurisdictions, meet international and national trade and safety standards and be supported by industry and consumers.

These committees are working to reduce the timeline in which new and higher energy efficiency standards are published from an average of five years to an average of two years. This will allow provincial and federal government regulators to react more quickly to opportunities of having higher efficiency equipment installed in new homes.

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New standards relevant to the new home market, which will be published this year and will be available for adoption in Nova Scotia, include: air-to-air heat pumps, geo-thermal heat pumps and electric and gas-fired water heaters. The relevant standards to new home construction, which have been given priority for updating this year and are expected to be published before 2013, are: packaged split system air conditioner / heat pumps and electronic thermostats.

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Request IR-37:

Custom C&I: Segments to be targeted in 2012 may include grocery stores, schools, large multi-family buildings, military and the high-tech industry, among others. (p.22 of 43)

Please explain what incentive levels and % of incremental costs would be covered by incentives that Custom C&I (and Small Business Direct Install) would consider for grocery stores retrofits, including current examples. As well, please indicate the strategic direction and timeline ENSC foresees in working with government to cost-effectively reduce electricity demand and increase efficiency in grocery stores through codes and standards for refrigeration (4.4).

Response IR-37:

The C&I Custom program provides incentives calculated as the lowest of:

- $0.15 per kWh of annual electrical energy savings
- 50 percent of customer implementation costs
- the amount resulting in a simple payback meeting customer investment criteria (to a minimum simple payback of one year).

The Small Business Direct Install program currently provides incentives covering up to 80 percent of customer implementation costs for lighting retrofits. For 2012, refrigeration measures may be added to this program.

The steering committee on Performance Energy Efficiency and Renewables (SCOPEER), and its affiliated SCOPEER Resource Task Force (SRTF) have identified commercial refrigeration as a high priority. ENSC, as a member of the SRTF, will contribute funding this year to review the

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opportunities for energy savings from commercial refrigeration equipment. The resultant study will be used to assess the need for higher efficiency standards, the need for revisions to existing standards for the purpose of harmonization with the USA/California standards, and the opportunity for energy savings, federally and provincially.

The review will be completed in the summer of 2011 and it is expected that the technical sub-committee on commercial refrigeration will be able to begin updating standards in 2012. ENSC will then be able to begin market transformation programs in commercial refrigeration, in anticipation of a new standard being available for reference in regulation, by 2014.

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Request IR-38:

Development and Research: ENSC will focus on emerging energy-efficiency strategies and technologies. (p.33 of 43)

Please provide information with regards to what ENSC deems to be 'emerging energy-efficiency strategies and technologies' based on existing knowledge.

Response IR-38:

Emerging technologies might include, for example, LED lighting or cold-climate heat pumps. Emerging strategies are meant to encompass innovative or promising new strategies or concepts not currently conceived of, but that could be worthy of further examination and/or field-testing, to determine their ability to maximize savings and/or minimize costs.

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Request IR-39:

What process will ENSC utilize to identify and prioritize new strategies and technologies?

Response IR-39:

ENSC will keep abreast of new technologies and strategic opportunities through the use of its staff and consultants. ENSC has not adopted a specific process to prioritize strategies and technologies. It will use guiding principles, presented in the 2012 DSM Plan, to inform decisions regarding new strategies and technologies.

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Request IR-40:

What level of engagement will ENSC have with stakeholders with respect to development and research focus on strategies and technologies?

Response IR-40:

ENSC welcomes input from stakeholders. The Program Development Working Group (PDWG) currently provides the opportunity for stakeholders to engage in this regard. The future role of the PDWG is on the issues list for the 2012 DSM Plan Hearing. ENSC is also using other mechanisms to engage stakeholders who have not previously been active in the regulatory process for electricity DSM.

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Request IR-41:

Codes and Standards: A number of opportunities are emerging in the residential and commercial sectors for ENSC to support and promote new energy codes and standards. (pg.34 of 43)

Please explain how ENSC will identify and assess opportunities to work with government to develop and enforce new codes and standards in the residential and commercial/industrial sectors, and what opportunities (beside those already identified) ENSC foresees as potential areas of interest.

Response IR-41:

ENSC will keep abreast of new opportunities, through its staff (including ongoing communications with government) and its consultants. ENSC will also identify and assess codes and standards opportunities through its participation in federal and/or provincial committees and working groups focused on regulatory opportunities. ENSC may also contribute to baseline studies to examine compliance or other related issues. The opportunities identified in the 2012 DSM Plan are areas of interest on the immediate horizon and ENSC anticipates others to develop over time.

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Request IR-42:

On May 19, 2010, a one-day session was organized to discuss the effects of free ridership and participant spillover with respect to DSM energy savings in Nova Scotia. The session was attended by NSPI, Navigant, consultants for the UARB and PDWG, the evaluation consultant and experts from other jurisdictions. The outcome was an approach for evaluating free ridership and spillover. This approach was communicated to stakeholders through the PDWG, and at a stakeholder technical conference held on November 30, 2010. It provided direction to the independent evaluation firm for evaluating DSM results starting in 2010. ENSC intends to refine the evaluation of free ridership and spillover as programs evolve. (p.18)

Please provide any documents and information with respect to how ENSC is proposing protocols for handling free-ridership and spillover.

Response IR-42:

Please refer to Multeese IR-12c.

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Request IR-43:

How has ENSC considered the issues of free-ridership and spillover in developing their 2012 savings estimates?

Response IR-43:

Net-to-gross is the combined effect of free-ridership and spillover. ENSC used the following net-to-gross ratios in determining the 2012 savings estimates:

2012 DSM Program	Net-to-Gross Ratio
Efficient Products	0.85
Existing Houses – non-Low Income	0.80
– Low Income	1.00
New Houses – EnerGuide 83	0.60
– EnerGuide 84	0.65
– EnerGuide 85	0.70
– EnerGuide 86	0.75
– EnerGuide 87	0.80
– EnerGuide 88	0.85
– EnerGuide 89	0.90
Home Energy Report	1.00
Prescriptive	0.90
Custom	0.90
Small Business Direct Install	0.99