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Providing insights that enable evidence-based, data-driven decisions

Insights from Smart Meters:
Identifying specific actions, behaviors, and characteristics that drive savings in behavior-based programs

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Smart Meter Data: the Opportunity

Smart meters, smart thermostats, and other new technologies provide previously unavailable high-frequency and location-specific energy usage data. Many utilities are now able to capture real-time, customer specific hourly interval usage data for a large proportion of their residential and small commercial customers. These vast, constantly growing streams of rich data (or, "big data") have the potential to provide novel insights into key policy questions about how people make energy decisions.

What can we do with all of these data?
The richness and granularity of these data enable many types of creative and cutting-edge analytics. Technically sophisticated and rigorous statistical techniques can be used to pull useful insights out of this high-frequency, human-focused data. In this series, we call this "behavior analytics". This kind of analytics has the potential to provide tremendous value to a wide range of energy programs.

For example, disaggregated and heterogeneous information about actual energy use allows energy efficiency (EE) and/or demand response (DR) program implementers to target specific programs to specific households; enables evaluation, measurement and verification (EM&V) of energy efficiency programs to be performed on a much shorter time horizon than was previously possible; and may provide better insights into the energy and peak hour savings associated with EE and DR programs (e.g., behavior-based (BB) programs).

In this series,
"Insights from Smart Meters", we present concrete, illustrative examples of findings from behavior analytics research using these data that are immediately useful and relevant, including:

- **Proof-of-concept analytics techniques** that can be adapted and used by others;
- **Novel discoveries** that answer important policy questions; and
- **Guidelines and protocols** that summarize best practices for analytics and evaluation.

The goal
of this series is to enable evidence-based and data-driven decision making by policy makers and industry stakeholders, including program planners, program administrators, utilities, state regulatory agencies, and evaluators. We focus on research findings that are immediately relevant.

Focus on: identifying actions that drive savings

In this report, we use smart meter data to analyze specific actions, behaviors, and characteristics that drive energy savings in a behavior-based (BB) program. Specifically, we examine a Home Energy Report (HER) program. These programs typically obtain 1% to 3% annual savings, and recent studies have shown hourly savings of between 0.5% and 3%.[1]

But what is driving these savings? What types of households tend to be "high-savers", and what behaviors are they adopting? There are several possibilities: one-time behaviors (e.g., changing thermostat settings); reoccurring habitual behaviors (e.g., turning off lights); and equipment purchase behaviors (e.g., energy efficient appliances), and these may vary across households, regions, and over time.

Why does this matter?
While HER programs are increasingly adopted nationwide, there is surprisingly little clarity about what is driving the savings achieved by these programs. An analytics method that uses easily available data to provide insights into savings behaviors can help utilities, regulators, and policymakers:

Analytics Technique

Smart meter data allows us to unpack behaviors that drive energy savings.

Key Results

Our results suggest that behaviors related to air conditioning (AC) drive savings for our program rollout.

- All households save energy, but AC households save more overall, during peak hours, and on hot days. They represent 60% of households but provide 81% of peak savings.
- Targeting AC households may lead to higher savings and increased cost effectiveness.

- **Shed light on measure life, persistence and attribution issues,** *which are currently not well understood for HER programs;[2]*

- **Lead to improved HER program design,** *where programs are continuously modified and tailored for each household, increasing program effectiveness; and*

- **Increase the cost-effectiveness of these programs by identifying and targeting "high-saving" households,** *allowing more efficient use of ratepayer money.[3]*

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[1] See: Integral Analytics (2012), KEMA (2012), Allcott (2011), Opinion Dynamics (2012), Todd et al. (2014), Stewart (2013)

[2] For example, installing LED lighting may imply that savings persist for years, but cause attribution issues where savings is "double counted" for both the BB program and an EE lighting program. Turning off lights may imply different issues.

[3] Targeting may be particularly useful for programs focused on peak hour savings, or those in regions where the program is marginally cost-effective based on pilot results. Cost-effectiveness also should account for the marginal cost per household.

Analytics Technique: Proof-of-concept

Several studies have attempted to identify actions related to savings from HERs using surveys and information from rebate programs – mostly obtaining inconclusive results.[4] While it is possible to observe the uplift in utility program participation that results from exposure to HERs, it is impossible to observe changes in other important behaviors using information about participation in utility rebate programs. Efforts to observe changes in other household behaviors have typically employed population survey techniques. Unfortunately, information obtained from surveys is of limited value for the following reasons:

- In order to detect actions that account for a small savings effect, a very large and representative number of survey responses is required from both the control and treatment groups. The cost of obtaining enough responses may be prohibitive; and worse, there is never a guarantee that response rates will be high enough.

- The subset of people who choose to respond to surveys may be inherently different than those that do not, and the results from this subset of survey responders may not be generalizable to the entire program population.

- Surveys can be prone to self-report bias because of misinformation and recall errors. For example, people may not accurately remember the actions that they took or may not accurately understand the efficiency of their own appliances.[5]

- Survey responses concerning energy use may be especially prone to social desirability response bias: people may bend the truth or respond strategically so that their answers conform to what they believe they *should* be doing.[6]

- Surveys concerning BB programs may be particularly susceptible to non-response bias: energy topics may be more salient for households in the treatment group, which may make them more likely to respond to the survey than the control group.

All of these may lead to incorrect conclusions about savings behaviors.

We provide an alternate method for analyzing savings behavior using smart meter data, rather than relying on survey data. We use analytical techniques to unpack the hour-by-hour savings into savings related to AC usage (heretofore untried in this context). First, we segment households into those that have a high

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[4] See Opinion Dynamics (2012), Smith and Arnot (2014), Integral Analytics (2012), Allcott and Rogers (2013)

[5] E.g., Allcott (2014) reports that 50% of people responded in a survey that they purchased an Energy Star water heater, when in fact only 3% had.

[6] For example, continuously receiving letters which indicate that you are using more energy than your neighbors may encourage you to say that you only set your air conditioning to 78 even though you set it to 74.

likelihood of using AC ("AC households") and those that do not ("Non-AC households"), and examine the difference in savings for these two groups.[7] We then examine the overall savings separated by temperature into the hottest and coldest days in our sample. Our regression technique compares the electricity use of the treatment group to the electricity use of the control group jointly for each hour of the day, and includes interaction variables that allow us to estimate savings for AC and Non-AC households, on hot and cold days.[8]

Because these techniques rely on hourly energy usage data derived from smart meter applications rather than survey responses, they are not prone to self-report and social desirability bias, and are cheaper and easier to implement (once the analytical infrastructure is in place). However, analytic techniques may be prone to other forms of bias; all analyses rely on assumptions, some of which are more believable than others.[9]

We use data from one particular program rollout as a test-case: we draw upon electricity data from the Pacific Gas & Electric (PG&E) smart meter system to analyze the hour-by-hour impacts of a Home Energy Reports behavior-based program.

The design of this HER program involves mailing letters to households on a monthly or bi-monthly basis. The letters provide information about the household's energy use in addition to how their energy use compares to their neighbors. The letters also include some energy savings tips. These HER programs are designed as randomized controlled trials (RCTs): households are randomly assigned to either the treatment group that receives the letters, or the control group that does not. A well-designed RCT is the "gold standard" of program evaluation design, and thus allows us to produce unbiased estimates of the energy savings during each hour.[10]

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[7] The households are categorized as likely or not likely to use AC based on a model that estimates the likelihood that each household owns and uses AC.

[8] More details about the analysis specification are in the Appendix. We used difference-in-averages estimators with dummy variables that indicated treatment during each hour of the day, interaction variables that indicated treatment and AC during each hour of the day, and interaction variables that indicated treatment, AC, and hot days during each hour of the day. To account for correlation within customers but across days and hours, the standard errors are robust and clustered at the household level. Because of computing limitations, we maintained unique observations for each customer, but we aggregated all weekday data within a week for each hour, so that there were 24 hourly observations per week for each customer.

[9] The type of bias and error depends on the model, analysis, and assumptions used. For example, randomized experimental methods must be correctly randomized and correctly analyzed in order to be unbiased; estimates that do not use randomized experimental methods may be biased if assumptions about the control group are not correct; predictive models that estimate air conditioning usage may pick up noisy signals or signals that are confounded with other energy uses. It is our opinion that bias and error from energy data is likely to be less severe and more easily managed and mitigated than survey data.

[10] In addition to RCTs, there are other factors that are needed to produce valid energy savings estimates; see Todd et. al 2012.

We analyze hourly interval electricity consumption data for one particular HER program pilot rollout (called "Wave One" by PG&E). It includes 500,000 households in the top three quartiles of energy use, drawn from most geographic regions in PG&E's service territories.[11] Although it was not a full scale rollout, this large-scale pilot may be representative of households targeted in a full scale rollout at PG&E.[12] The PG&E Wave One rollout began on February 2012, but only three months of data were made available for this analysis: August 1st - October 31st 2012. This period includes 6 of the 10 highest hourly consumption levels in 2012.[13]

Analytics Technique: Unpack savings for AC and Non-AC households

We provide proof-of-concept of an analytics technique that uses smart meter data and other easily accessible data to provide insights into characteristics and behaviors that drive savings. This example unpacks the hour-by-hour savings into savings related to AC usage.

Implication: This technique may help us understand what drives savings in BB programs. It can be used by program implementers and evaluators as an alternative to other traditional techniques (such as customer surveys), and may lead to increased cost-effectiveness through targeting "high-saving" households, a better understanding of persistence and attribution issues, and more effective program design.

For the treatment and control group, we use data that identifies households that are likely to use air conditioning (AC) in order to form our two groups of AC and non-AC households. These households are identified through a model that uses monthly billing data in addition to other easily accessible public data sources in order to estimate the likelihood of owning and using air conditioning. The model was developed by Nexant for PG&E prior to this study.[14]

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[11] There were also two additional pilot "waves" of HERs that went out to different portions of the PG&E residential population previous to Wave One: Beta Wave and Gamma Wave. The Gamma Wave includes fewer households (~150,000), in all quartiles of energy use in a smaller geographic region, and the Beta Wave includes even fewer households (~120,000) in only the top quartile of energy use in an even smaller geographic region. For other reports we will use other data.

[12] A full scale rollout would likely also exclude the lowest energy use households because they typically yield lower savings that may not result in a cost-effective program offering to such customers.

[13] The highest consumption levels were determined based on ranking the hourly system retail load for 2012.

[14] The model was calibrated and informed using a Residential Appliance Saturation Survey (RASS), and does not use the HER survey data to calibrate the estimates. The model uses a probit specification, where the dependent variable is probability of AC usage and independent variables include data on energy usage prior to the program, temperature data, participation status in other PG&E programs, and census data on demographic information including income, age of population, age of house, number of people and children per household, and ethnic and racial background. For details on the model, see: Freeman, Sullivan & Co., April 1, 2010. *2009 Load Impact Evaluation for Pacific Gas and Electric Company's Residential SmartRateTM—Peak Day Pricing and TOU Tariffs and SmartAC Program, Volume 2: Ex Ante Load Impacts*. Prepared for Pacific Gas and Electric Company.

New Results: Insights from the data

First, we estimate the hour-by-hour savings from our test-case HER program. We segment each hour into savings for households estimated to be likely to use AC ("AC households") and those likely to not use AC ("Non-AC households"), using the analytics techniques discussed above. The results are shown in Figure 1 (along with the 95% confidence intervals).
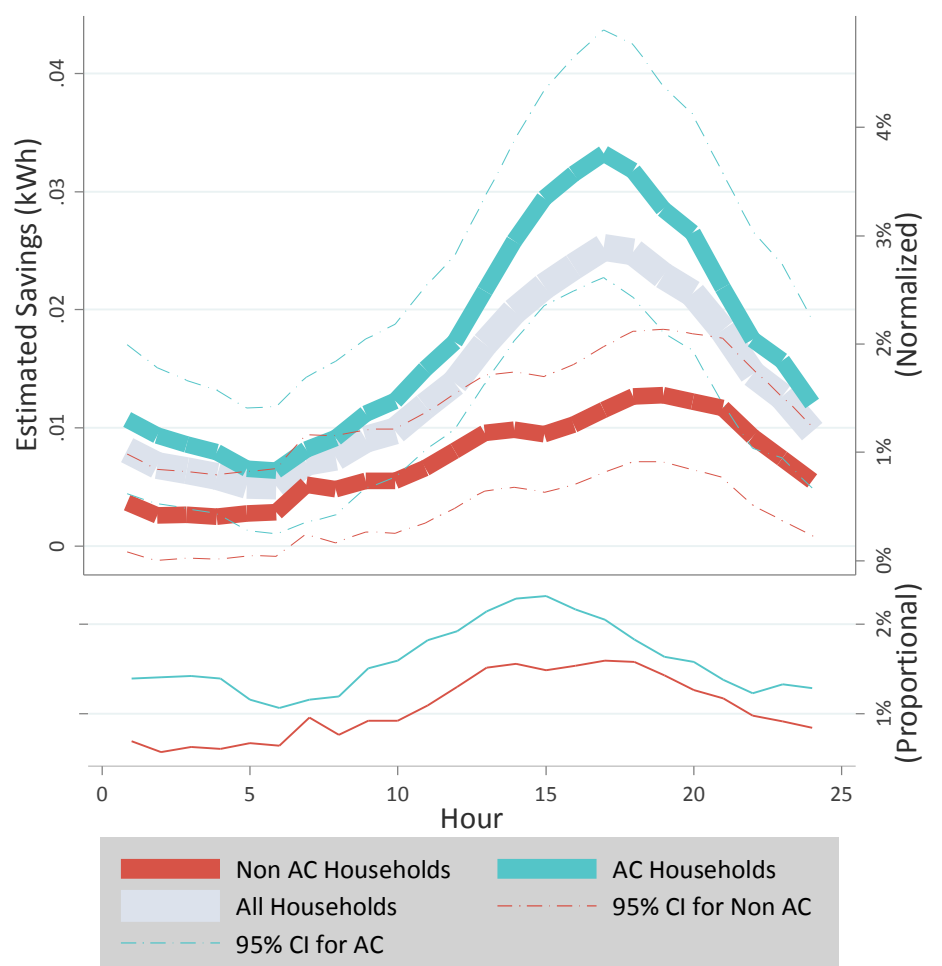
Figure 1. Savings for households likely to use AC and households not likely to use AC

We show three different scales: first, *kWh savings* (left y-axis on the top graph); second, *normalized savings* (right y-axis on the top graph) of the AC and non-AC treatment groups as a percent of the total average energy usage of the control group across all hours (in order to give a sense of how large the kWh savings are); and third, *proportional savings* (bottom graph) as a percentage of each hour's average energy usage for the AC and Non-AC control groups (to show the proportional savings relative to energy consumed each hour).

Key Result 1: AC households drive much of the savings

Our results in Figure 1 show one HER program with: [15]

- **Savings during (almost) every hour for both AC and Non-AC households;**
- **AC households save more overall**: an average AC household saves more than twice as much as a Non-AC household overall (2.3 times);
- **AC households save more during peak hours**: an average AC household saves almost 3 times as much (2.7 times) during peak hours (3-8pm);

AC households represent 60% of the population and use 67% of overall energy and 68% of peak hour energy, but provide 78% of the overall savings and 81% of peak hour savings.

Implication: Targeting households estimated to use AC may lead to higher overall and peak savings per household, increasing the cost effectiveness for this HER program.[16]

Next, we segment the savings even further into the ten hottest (i.e., highest temperature) and ten coldest (i.e., lowest temperature) days in our sample for AC and Non-AC households (see Figure 2).

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[15] Savings are statistically significant during each hour for AC and Non-AC households, except for Non-AC during hours 1-6. Peak savings for AC versus Non-AC households are statistically significantly different. All analysis results are shown in the Appendix.

[16] Our results unequivocally show that targeting households that are *estimated to use AC by the model* will lead to higher savings per household, regardless of whether the model estimates are correct. Targeting a limited set of households in order to increase cost effectiveness may be particularly useful for programs that are marginally cost-effective based on pilot results.
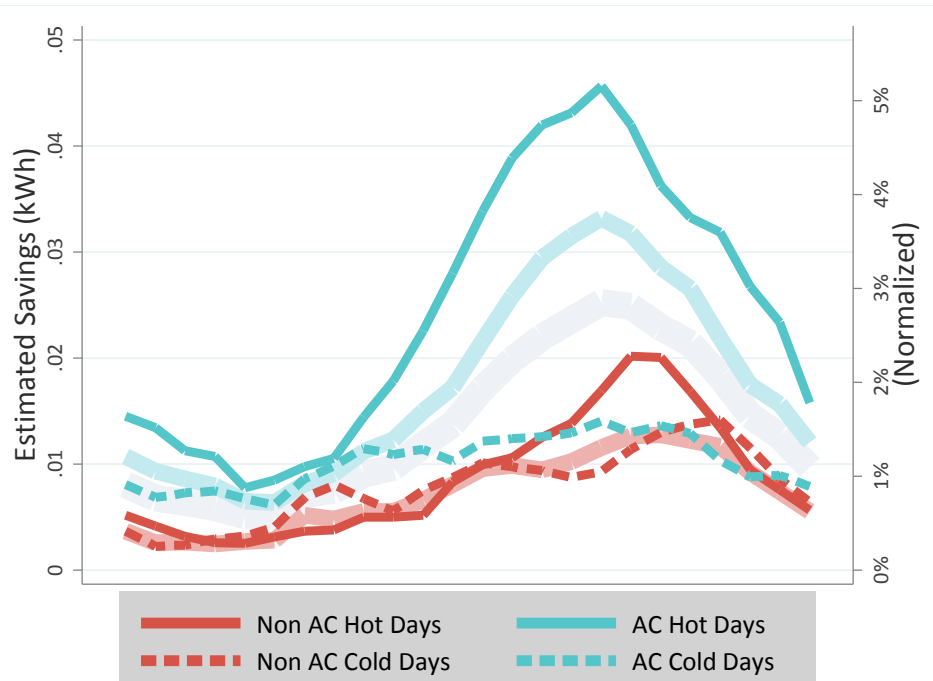
Figure 2. Hourly savings for the 10 hottest and 10 coldest days

The X and Y-axis scales are similar to the previous graph: first, *kWh savings*; second, *normalized savings* of the AC and non-AC treatment groups as a percent of the total average energy usage of the control group across all hours. For reference, Figure 2 also includes the savings from Figure 1 in lighter colors.

Key Result 2: AC households save more on hot days and peak hours

Figure 2 shows additional key findings: [17]

- For Non-AC households, savings during hot and cold days are similar;
- On cold days, savings for AC and Non-AC households are similar; and
- On hot days, AC households save more overall and during peak hours (3-8pm).

Implications:

- This evidence suggests behaviors associated with air conditioning may drive much of the savings achieved by this HER program rollout.[18]
- Our best guess is that people are changing their thermostat settings in order to save energy.[19] If true, this suggests that at least some of the savings is driven by one-time or habitual savings behaviors, rather than equipment purchases.
- Targeting households estimated to be likely to use AC may lead to higher savings during peak hours on the hottest days.[20]

However, there are still many issues that this research does not address. For example, while part of the savings may be driven by actions related to AC, our results clearly show that there are statistically significant savings for Non-AC households, savings during cold days, and savings during off-peak hours. This suggests that households are engaging in other behaviors unrelated to AC usage to also reduce their consumption.

In addition, these findings do not help us understand measure life and persistence issues. If thermostat settings are driving the savings, it is unclear whether this is a behavior that will last (and, if so, for how long), or if it will degrade over time.

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[17] Savings are not statistically significantly different during any hour for Non-AC households during hot days, for Non-AC households during cold days, and for AC households during hot days. Average savings and peak hour savings is statistically significantly higher for AC households on hot days than AC on cold, than Non-AC on hot, and than Non-AC on cold.

[18] These results show that households with AC save more than twice as much as non-AC households; it is unclear how much of the additional savings is due to AC usage and how much is due to actions correlated to AC usage.

[19] We could come up with other possible explanations of energy behaviors that are driving these savings. However, these behaviors would have to be highly correlated with AC usage. They would have to occur mainly in households with AC and would have to be highest on hot days during peak hours. We believe that AC behavior is the most likely.

[20] Even if the model that estimates AC usage is wrong, our results unequivocally show that targeting the households that are estimated to use AC by the model will lead to higher savings per household, and higher savings on hot days in peak hours, regardless of whether those households actually use AC or not.

These results may be specific to this particular program in this specific situation. Because we only have data from one utility (with a limited set of time-series data), we do not suggest that these results can be generalized and that all HER programs are driven by actions related to AC.[21] It is important to use these analytics methods to unpack the savings behaviors for other programs in order to draw broader conclusions about the actions and behaviors that are driving savings in HER programs.

Next Steps & Future Research

In this report we discussed analytic techniques that can be used to assess the impacts of AC usage on response to HERs. Our results also suggest that there are many other savings behaviors. Future research might use similar analytical techniques to examine other actions, behaviors, and household characteristics related to savings. For example, it may be interesting to look at savings related to water heaters, or households that have old or malfunctioning equipment to target for energy efficiency rebates.[22]

An interesting avenue of approach that should be tested in the future is the use of machine learning models for program targeting – using interval data to identify customers with high propensity for savings either through exposure to HERs or through exposure to conventional EE marketing programs. It would be very useful to compare the benefits of various targeting methods; for example, targeting AC households relative to targeting high pre-treatment usage households. Machine learning techniques might also be used to determine through the data which groups of people save the most, which may lead to further insights about behavior and actions that cause the savings.

We also believe that there is an exciting potential for deeper research into actions related to air conditioning. For example, households that have extremely low thermostat set points may have

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[21] In other words, even though the RCT design ensures that the results are *internally valid* (e.g., unbiased for a particular program, with a given participant population and a given time frame) does not mean that the results are *externally valid* (e.g., can be generalized and applied to new populations, circumstances, and future years).

In fact, Allcott (2014) shows that for Opower programs, the actions that drive the savings, and the persistence of savings vary widely across utilities and across customer groups, and that it is not possible to predict the savings. Instead, in order to understand how much savings was due to the BB program, and what actions were driving these savings, the program must be tested and analyzed for each utility, each customer group, and each year.

[22] For example, it may be possible to use hourly usage data together with temperature data, property assessor data on the type, square feet, and year of house, and other information to estimate the amount of energy required by the AC unit to produce one degree of cooling, and use that to estimate the likelihood that the unit is not as efficient as other units.

the highest potential for peak hour savings (in the summer); these households may be the most cost efficient households to target for recruitment into real time pricing programs. It would be interesting to use analytic techniques to detect thermostat set points and unpack the savings even further, and to verify our conjecture that changing thermostat set points may lead to savings. Additional future work could further segment the savings. For example, differentiating between different types of AC equipment (e.g., central vs. room), between AC usage in different climate zones, or between different types of housing (e.g., when it was built or how old the AC equipment is).

More research is needed to determine the implications of our findings for measure life, persistence, and attribution issues. If the savings are due to people changing thermostat settings, this behavior may last longer than savings due to habitual behaviors such as turning off lights, but may not be as stable or long lasting as investments in energy-efficient measures.

This series will continue to explore the kinds of insights which can be pulled from the newly available data captured by smart meters and other sources, and to report our key findings in future installments of *Insights from Smart Meters*.

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