What Behaviors Do Behavior Programs Change

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ABSTRACT

Utilities' behavioral programs, such as audits and web-based tools, are designed to change customers' energy consumption behaviors, and when evaluating the impact of such programs, the focus has been on the net energy savings achieved. In two recent evaluations of residential behavioral programs in California, we found that as these programs successfully change residential customers' energy consumption behaviors, and they also increase the rate at which the customers participate in other energy efficiency programs.

An analysis of residential participants of the Home Energy Efficiency Survey (HEES) audit program and a matched non-participant control group found that audit participants were significantly more likely to participate in other energy efficiency programs post-audit than the matched non-participants. Similar results were found from an analysis of Southern California Edison's SmartConnect® My Account and Budget Assistant (MA/BA) web presentment tool programs. Our research showed that, within half year after program enrollment, a customer is more likely to participate in energy efficient programs than the matched non-participant control group.

In both evaluations, the propensity score matching method was used to select the non-participant samples to match to the participants, so as to mitigate the potential self-selection bias. In both evaluations, the behavioral programs were found to increase future energy efficiency program participation, and the influence was statistically significant. We also found that the magnitude of the impact was much higher in the HEES program than in the MA/BA programs. The reason might be that the audit program actively provided more specific program information, whereas the MA/BA programs were not as focused.

Introduction

Utilities' behavioral programs, such as audits and web-based tools, are designed to change customers' energy consumption behaviors. Some programs introduce customers to other energy efficiency (EE) measures and programs, thereby helping them to reduce energy usage. Some programs provide information on customers' energy usage, stimulating them to reduce energy usage. Some programs suggest that the customers change their daily practices such as turning off lights when leaving the room, helping them to find more ways to reduce energy usage.

The evaluations of the behavioral programs have been focused on estimating the number energy efficiency measures bought by the customers, the uptake rates of the suggested energy-saving practices, the net-to-gross ratios and the reduction in energy bills. Although behavioral programs may increase the likelihood that customers participate in energy efficiency programs in the future, this change is not the focus of the program evaluations, and all the savings related to the energy efficiency programs are carefully excluded from the behavioral program evaluation, because the savings are claimed through energy efficiency programs.

However, it is important to know whether the behavioral programs can lead the customers to participate in energy efficiency programs or not. It helps the design and implementation of future behavioral programs, and helps the decision makers to coordinate among energy efficiency programs and behavioral programs.

In two recent evaluations of residential behavioral programs in California, we found that, as these programs successfully changed residential customers' energy consumption behaviors, and reduced their energy bills, they also increase the rate at which the customers participate in other energy efficiency programs. The two evaluations include the California Statewide Home Energy Efficiency Survey (HEES) programs, and Southern California Edison (SCE) SmartConnect My Account (MA) and Budget Assistant (BA) programs.

Introduction of the HEES Programs and SCE SmartConnect MA/BA Programs

CA Statewide Home Energy Efficiency Survey Programs

The residential Home Energy Efficiency Survey programs were introduced in 2010 statewide. The goal of this program was to help customers identify energy efficient measures and practices, educate residential customers about energy efficient measures and behaviors, and promote cost effective energy efficiency projects.

The HEES programs surveyed the participants online, through mail, on the phone, and on-site. Based on the survey results, HEES provided the participants with analyses of customer end-use systems, helped participants to identify EE program opportunities, and provided economic information for customers to make investment decisions. The HEES recommendations included suggestions for particular EE measures, the adoption of energy efficiency practices, and recommendations that were clearly linked to particular end uses.

HEES was also a conduit for increasing participation in other IOU energy efficiency incentive programs, providing direct support for and coordination with these programs.

SCE SmartConnect Customer Web Presentment and SCE Budget Assistant

My Account serves as SCE's online portal by providing customers that have been cut over to operations (COTO) access to their historical billing, payment, and electric usage data. It presents customers with their hourly energy usage information up to the previous day and provides them with forecasts of their current month's bill and estimates of their bills to date (i.e., Projected Next Bill and Bill-to-Date). Additionally, it allows customers to learn about and sign up for other Edison SmartConnect enabled energy saving programs (i.e., Budget Assistant and Save Power Day Incentive Alerts).

The first web presentment tool is "Projected Next Bill." This tool provides My Account customers with a forecast of their upcoming monthly energy bill based on past energy usage. Based on recorded usage, a daily average usage estimate, the remaining number of days within the current billing period, and the customer's rate, a forecast of the current (yet to be received) bill is provided.

The "Bill-to-Date" web presentment provides My Account customers with daily electricity usage information factored with retail rates for residential and small and medium (<200 kW) nonresidential customers. The cost estimate within the current billing period is updated daily through the previous day's usage.

Budget Assistant is a proactive notification tool that provides customers with weekly or conditional notifications regarding costs within their current billing period. Notifications are sent through the channel of customer choice (email, text message, or voice message). Enrolled customers receive either weekly performance notifications of progress toward a selected monthly spending target or a notification when a pre-specified spending goal is reached. Budget Assistant customers can also enroll in My Account. Dual enrollment in both Edison SmartConnect tools provides Budget Assistant participants with access to tools providing them visual tracking of their progress toward their spending goal on a daily basis.

Self-Selection Bias and Non-Participant Sample Selection

This study modeled the probability of future energy efficiency program participation as a function of current behavioral program participation along with other relevant factors. To assess the behavioral responses by participating customers and controls for larger economic effects, it requires a carefully developed non-participant sample.

Ideally, an experimental design would be used to determine the influence of a program on household behavior. Using an experimental design, households would be randomly assigned to participant (treatment) and non-participant (control) groups. If an experimental design methodology had been used to determine program participation, random assignment would ensure that the economic characteristics of the control and participant households would be approximately equivalent. Consequently any differences between treatment and control groups in the rate of participation in EE programs would be reasonably attributable to participation in the audit.

Participation in the HEES programs, and the MA and/or BA programs, however were voluntary. Given that individuals chose their program participation, the participant and non-participant groups were likely to differ systematically. The participant and non-participant groups are observably different: one group self-selected to participate in the programs and one group did not. The self-selection is likely to be associated with other important differences that exist between participant and non-participant households that could help explain the participation choice and associated energy efficiency program participation choices of these households.

For example, a household that has recently decided to reduce its carbon footprint is likely to be looking for ways to reduce its energy usage. As they take steps to reduce their energy usage, they may sign up for HEES, My Account, and/or Budget Assistant to help achieve their goal of using less energy. For the same reason, they may sign up for energy efficiency programs, too. The decision of energy efficiency program participation would be due to their decision to reduce their carbon footprint and would not be attributable to the impact of their participation in the behavioral programs. Without a randomly selected control group with similar attitudes towards reducing carbon footprints, the analysis methodology cannot separate the energy efficiency participation due to the behavioral programs from the participation choice due to their changing views on carbon footprints. In this example, the lack of a randomly selected control group would lead to an inflated estimate of the influence of the behavioral programs.

The lack of an experimental design for these programs makes the accurate estimation of the influence of the programs difficult, if not impossible to determine. The solution is what is called a quasi-experimental matching method. Using matching methods to choose the non-participant households can partially control the selection bias from voluntary participation. Matching methods, however, rely on two key assumptions to replicate analyses that would be undertaken as controlled experiments. First, matching methodologies assume that differences which lead households to participate in the program can be fully described by observable characteristics in the participant and non-participant populations. The second requirement for matching methods is that the study can be divided into two clear stages: a design phase and an analysis phase.

Turning to the first assumption, the ability to correctly characterize program participation with observable variables can never be proven and the existence of unobservable characteristics that are correlated with both behavioral program participation and energy efficiency program participation may lead to bias in analyses using matching methods.

It is not clear that the behavioral programs in this study represent a situation where the potential bias from matching on observable characteristics will sufficiently minimize the relative size of potential bias. Consider the example of the household that has recently decided to reduce their carbon footprint. This household was more likely to sign up for both behavioral programs and energy efficiency programs. Comparing the probability of future energy efficiency participation of this household with the probability of future energy efficiency participation among other households not participating in the behavioral programs is likely to overstate the impact of the behavioral programs. Matching methods could be used to choose a "matched" group of non-participant control households. The household characteristics available to select a matched non-participant control group would necessarily be based on observable characteristics. The observable household characteristics include past program participation, household geographic location, usage, the seasonal distribution of usage, and other possibly relevant factors. Matching on these observable characteristics would likely reduce the potential bias in the estimate of the program's impact. The reduction in bias is due to the assumption that households with similar observable characteristics also have similar views on carbon footprints. If, in our example, it is reasonable that after controlling for these observable characteristics there is no remaining correlation between signing up for the behavioral programs and recent views on carbon footprints, then there is no sample selection bias remaining due to a household's views on carbon footprints. It is not clear if it is valid in this example to assume that controlling for observable characteristics eliminates meaningful correlations between unobservable characteristics and signing up for the behavioral programs.

The second requirement for a matching methodology is that there must be two clear stages to the study. The first stage must be a clearly observable design stage where the households can be compared prior to any potential program impact. The design stage is needed to match households on observable characteristics that have not been impacted by the programs. The second stage is the analysis stage, where the potential program impact can be estimated.

Fortunately, both the HEES programs and the Edison SmartConnect MA/BA Program can be fashioned into a two-stage experiment. The design stage includes the one year period prior to program participation. The matching methodology will use the observable household characteristics from this period. The analysis phase includes a six-month period following the program participation. The probability of energy efficiency participation of the behavioral program customers is compared to the probability of the energy efficiency participation in the control group in this period of time.

Propensity Score Matching Method

The propensity scoring methodology (PSM) uses observable classification variables in a logit model to estimate the probability of participation within the participants and non-participants based on pre-program period observable characteristics. The characteristics include: 1) the first and second order of monthly usage (kWh) in the 12-month period prior to participation; 2) the correlations between the monthly usage and the weather variables (CDD and

HDD)[1]; 3) a series of geographic dummy variables; 4) past energy efficiency program participation in the 12-month period prior to the behavioral program participation; and 5) a series of dummy variables indicating the tariff rate of the household: CARE, FERA, TOU, SDP, etc.

Using logistic regression, propensity scores were estimated for program participants and non-participants. This propensity score represented the probability of participating in the behavioral program. Non-participants with similar scores to the participants were selected as non-participant matches.

Table 1 below presents the comparison between HEES participants and non-participants before and after the matching. The italicized numbers below the non-participant statistics are the significance level of the t-test for the hypothesis that the participants and the non-participants come from the same sample.

As shown in Table 1, before matching, participants were likely to be larger energy consumers, and were more likely to participate in energy efficiency programs. Since the larger consumers have more incentives to save energy and lower their bills, they are more likely to participate in both behavioral programs and energy efficiency programs. If the analysis include larger participants and smaller non-participants, it is very likely to attribute the larger consumers' energy efficiency program participation to HEES, and hence overestimate the impact of the program.

Table 1. Comparison of key variables for the HEES participants and non-participants before and after PSM matching

	Pre Matching		**Post Matching**	
	Participants	**Non-Participants**	**Participants**	**Non-Participants**
HEES PG&E				
Mean Monthly Usage	845	672	846	847
		<.0001		*0.6475*
Past EE Participation	4.8%	2.1%	4.8%	4.6%
		<.0001		*0.1451*
Propensity Score	0.02	0.01	0.02	0.02
		<.0001		*0.9992*
# Sites	23,080	396,491		22,668
HEES SCE				
Mean Monthly Usage	734	661	734	737
		<.0001		*0.1292*
Past EE Participation	6.5%	1.8%	6.5%	5.3%
		<.0001		*<.0001*
Propensity Score	0.03	0.01	0.03	0.03
		<.0001		*0.9997*
# Sites	48,937	862,047		47,710

After matching, the key variables of participants and non-participants become much more alike. Note that the match was based on the propensity scores, and the other factors may not get perfectly matched. Say, for example, the prior energy efficiency participation rates are still statistically different for the HEES SCE participants and non-participants. One possible explanation is that the prior energy efficiency program and the HEES participation were not highly correlated, and the matched HEES non-participant sample does not need to perfectly

[1] These variables are used to measure the sensitive of the energy usage to the weather change.

resemble the participants in terms of prior energy efficiency participation. An extreme case is that one factor is perfectly correlated with the modeled program participation, and hence when matching based on the participation probabilities, the factor has to be matched perfectly. On the other hand, if a factor has no correlation with the modeled program participation, the post PSM non-participant sample should keep the same as the pre-matching sample in terms of this factor. The prior energy efficiency participation is something in between. The PSM selected a non-participant sample similar to the participant sample in terms of prior energy efficiency participation, but not exactly the same.

Table 2 below reports the comparison between SCE SmartConnect My Account and Budget Assistant participants and non-participants before and after the matching. The italicized numbers below the non-participant statistics are the significance level of the t-test for the hypothesis that the participants and the non-participants come from the same sample.

Table 2. Comparison of key variables for the SCE SmartConnect my account and budget assistant participants and non-participants before and after PSM matching

	Pre Matching		**Post Matching**	
	Participants	**Non-Participants**	**Participants**	**Non-Participants**
Budget Assistant				
Mean Monthly Usage	602.8	573	602.7	628.1
		<.0001		*<.0001*
Past EE Participation	7.3%	3.5%	7.3%	6.7%
		<.0001		*<.0001*
Survey Program Participation	2.9%	0.8%	2.9%	2.4%
		<.0001		*<.0001*
Propensity Score	0.0927	0.0544	0.0926	0.0926
		<.0001		*1.0000*
# Sites	112,623	5,530,471		122,582
My Account				
Mean Monthly Usage	639.2	573	639	630.2
		<.0001		*<.0001*
Past EE Participation	5.6%	3.5%	5.6%	5.4%
		<.0001		*0.0004*
Survey Program Participation	1.9%	0.8%	1.9%	1.8%
		<.0001		*0.0377*
Propensity Score	0.0856	0.0544	0.0855	0.0855
		<.0001		*1.0000*
# Sites	257,150	5,530,471		257,071

Table 2 shows similar findings as in Table 1 that larger customers were more likely to participate in the MA and/or BA programs, and that prior energy efficiency participants and prior survey program participants also had higher probability to participate in the behavioral program. The matched non-participant sample exhibits more similar statistics as the participants, but the matched sample is still statistically different than the participant sample in terms of energy consumption level, the prior energy efficiency participation and the prior survey program participation.

The statistics from Table 1 HEES SCE are very different than the numbers in Table 2. Although both are SCE's programs, they differed in time and location. On average, HEES program was earlier than the MA/BA program, and MA/BA sample excluded the areas where Smart Meters were not operationalized and/or the MA/BA enrollments were low, while the HEES program was available throughout the whole SCE service territory.

Logit Model

To estimate the change EE program participation attributable to participation in the behavioral program, a logit model was employed to estimate the probability of participation in future energy efficiency programs using the matched sample data for the participants and non-participants of the behavioral program. For each behavioral participant and matched non-participant account, the EE tracking data was used to determine if the account had participated in a traditional EE program following the behavioral program. For the participant sample, a participant was considered as a future EE participant if he or she adopted any EE programs within six to twelve months after the behavioral program participation. For the non-participant sample, EE program participation was defined as having participated in EE programs within six to twelve months after the matching period.

Independent variables for the MA/BA analysis included in the model to estimate EE program participation are all indexed by site (*i*). Examples of some of these variables are as follows:

- **$MA\_Participation_i$**: This variable equals 1 if the account has participated in the My Account Program post COTO. The variable is zero otherwise.
- **$BA\_Participation_i$**: This variable equals 1 if the account has participated in the Budget Assistant Program. The variable is zero otherwise.
- **$PriorEEPart_i$**: This variable equals 1 if the account participated in SCE energy efficiency programs prior to the SmartConnect program participation period for SmartConnect participants or prior to or during the matching period for SmartConnect non-participants. The variable is zero otherwise.
- **$PirorSVPart_i$:** This variable equals 1 if the account participated in SCE Home Energy Efficiency Audit prior to the SmartConnect program participation period for SmartConnect participants or prior to or during the matching period for SmartConnect non-participants. The variable is zero otherwise.
- **RSD_Usage_i, $CorrHDD_i$, $CorrCDD_i$, $kWh_{i,m}$ $\{m=1,\ldots,12\}$:** These are the statistics of the electricity consumption in 12 months prior to the SmartConnect program participation period for SmartConnect participants or prior to or during the matching period for SmartConnect non-participants. For each account *i*, RSD_Usage was the relative standard deviation of the 12-month usages, CorrHDD and CorrCDD were the correlation of weather variables and the electricity usages, and kWh_m $\{m=1,\ldots,12\}$ were the 12- month usages.
- **$FERA_i$, $CARE_i$, TOU_i, SDP_i:** These are a set of variables that equal 1 if the account is in FERA, CARE, TOU or SDP rate. The variable is zero otherwise.

Independent variables for the HEES analysis included **$PriorEEPart_i$**, **RSD_Usage_i, $CorrHDD_i$, $CorrCDD_i$, $kWh_{i,m}$ $\{m=1,\ldots,12\}$**, and **$FERA_i$, $CARE_i$, TOU_i, SDP_i**, too. Here, the behavioral program effect is **$HEES\_Participation_i$**.

HEES Model

$$
\begin{aligned}
Prob(EE\ Participation)_i & \\
= \beta_1 + \beta_2\, HEES\_Participation_i + \beta_3\, PriorEEPart_i + \beta_4\, CARE_i + \beta_5\, FERA_i \\
+ \beta_6\, TOU_i + \beta_7\, RSD\_Usage_i + \beta_8\, corrHDD_i + \beta_9\, corrCDD_i \\
+ \sum_{t=JAN}^{DEC} \beta_{10}^{t}\, kWh_{i,t} + \varepsilon_i
\end{aligned}
$$

<u>MA/BA Model</u>

$$
\begin{aligned}
Prob(EE\ Participation)_i & \\
= \beta_1 + \beta_2\, MA\_Participation_i + \beta_3\, BA\_Participation_i + \beta_4\, PriorEEPart_i \\
+ \beta_5\, PriorSVPart_i + \beta_6\, CARE_i + \beta_7\, FERA_i + \beta_8\, TOU_i + \beta_9\, SDP_i \\
+ \beta_{10}\, D\_MoreAcct_i + \beta_{11}\, RSD\_Usage_i + \beta_{12}\, corrHDD_i + \beta_{13}\, corrCDD_i \\
+ \sum_{t=JAN}^{DEC} \beta_{14}^{t}\, kWh_{i,t} + \sum_{s=2}^{41} \beta_{15}^{s} SampleDummy_{i,s} + \varepsilon_i
\end{aligned}
$$

The β_2 in the HEES model and the β_2 and β_3 in the MA/BA model are the main variables of interests. They describe the impact of behavioral program participation on the probability of future energy efficiency program participation. The estimated parameters, after transformation, can be interpreted as the marginal increase in the probability EE participation associated with the behavioral program.

Regression Results

Table 3 below reports the key parameter estimation for the HEES SCE regression model. The D_Long through D_Tel are a set of variables that equal to one if the account participated in the HEES program through on-site audit, telephone audit, mail-in audit, long version online audit, and short version online audit, respectively. The top half lists the regression results that model the impact on the energy efficiency program participation within six months of the behavioral program participation, and the bottom half lists the results for the impact on the EE program participation within one whole year after the behavioral program participation.

Table 3. Key parameter estimates for the HEES SCE model

Variable	Estimate	StdErr	ProbChiSq	MarginalEffect
Dep Var=1 if participate in EE within 6 months				
Intercept	-4.2118	0.0962	<.0001	-0.1084
PriorEEPart	0.1473	0.0932	0.1139	0.0040
D_OnSite	1.0393	0.1648	<.0001	0.0442
D_Tel	0.9954	0.1979	<.0001	0.0415
D_Mail	0.4931	0.0490	<.0001	0.0141
D_Long	0.7372	0.0543	<.0001	0.0239
D_Short	0.6804	0.1258	<.0001	0.0241
Dep Var=1 if participate in EE within 12 months				
Intercept	-3.6606	0.0736	<.0001	-0.1650
PriorEEPart	0.0991	0.0723	0.1702	0.0047
D_OnSite	0.8511	0.1344	<.0001	0.0561
D_Tel	0.8838	0.1570	<.0001	0.0592
D_Mail	0.5216	0.0363	<.0001	0.0260
D_Long	0.6181	0.0421	<.0001	0.0335
D_Short	0.7020	0.0940	<.0001	0.0429

The column "ProbChiSq" lists the significance level of the corresponding parameter. It can be seen from the table that the HEES programs, no matter what delivery mechanism was adopted, increased the probability of future EE program participation, and the effects were statistically significant. The effects are relatively higher for the on-site and telephone participants than for the mail-in and online participants. On the other hand the prior energy efficiency participation is only marginally significant, and the estimated parameters are smaller, too. The qualitative findings remain the same for both six-month model and one-year model.

To quantify the marginal effect of the HEES participation on the probability of future EE program participation, it is necessary to use the estimated parameters to calculate the probability of future energy efficiency participation when the account is not a HEES participant and then compare it with the probability of participation when the account is a HEES participant. The Marginal Effect column in Table 3 presents the estimated marginal effects associated with being a HEES participant.

First, focus on the top part of the table. Six months after participated in the HEES program[2], the probability of energy efficiency participation is 2.7%. The HEES on-site participants' probability of participating in future energy efficiency programs is higher than the households who never participated in HEES by 4.4%, comparing to the underlying probability, the HEES on-site audit almost tripled the probability of future energy efficiency program participation. The HEES by other delivery mechanism also increased the probability of future energy efficiency program participation. The telephone audit increased the energy efficiency program participation by 4.2%, the mail-in audit increased the probability by 1.4%, and the long version and short version of online audit increased the probability by 2.4% and 2.4%, respectively. On the other hand, prior energy efficiency program participants' probability was only 0.47% higher than the households who had no experiences in energy efficiency programs before.

One whole year after HEES participation[3], the probability of energy efficiency program participation is 4.8%. The lower part of Table 3 shows that the on-site HEES participants' probability of participate in energy efficiency program in this year is 5.6% higher than the households who did not participate in HEES, and the telephone audit increased the participation probability by 5.9%, the mail-in audit increased the probability by 2.6%, and the long and short version of online audit increased the probability by 3.4 and 4.3%, respectively. Comparing to those big changes, prior energy efficiency program experience only increased the future participation probability by 0.47%.

Comparing the six and 12 month results in Table 3, one can find that the marginal effects were higher for the six month model, which shows that the HEES programs led to more energy efficiency program participation even after six months. But when considering the underlying EE program participation probability, it is clear that the impact diminished as time went by. The prior energy efficiency program experience had the similar effects, but the magnitude was much smaller.

Table 4 below reports the key parameter estimation for the HEES PG&E regression model. PG&E only provided HEES through online audit, and is denoted using the as HEES_Part in the table. The variable equals to one for the HEES participants and zero otherwise.

[2] For the non-participants, this is six months after the matching period.

[3] For the non-participants, this is one whole year after the matching period.

Same as in Table 3, the column "Estimate" is the parameter estimation and the column "ProbChiSq" lists the significance level of the corresponding coefficients. It can be seen from Table 4 above that the HEES programs increased the probability of future EE program participation, and the effects were statistically significant at the 1% significance level. For the HEES PG&E model, prior EE program experience also positively impacted the customers' probability of future EE program participation, and the effect was statistically significant.

Table 4. Key parameter estimates for the HEES PG&E model

	Variable	Estimate	StdErr	ProbChiSq	MarginalEffect
Dep Var=1 if participate in EE within 6 months					
	Intercept	-3.6442	0.1076	<.0001	-0.1683
	PriorEEPart	0.2715	0.0890	0.0023	0.0140
	HEES_Part	0.7473	0.0459	<.0001	0.0334
Dep Var=1 if participate in EE within 12 months					
	Intercept	-2.9883	0.0840	<.0001	-0.2194
	PriorEEPart	0.1653	0.0737	0.0249	0.0129
	HEES_Part	0.5695	0.0354	<.0001	0.0412

The last column in Table 4 lists the marginal effects of the corresponding dummy variables. According to the upper part of Table 4, the HEES participants are 3.3% more likely to participate in EE programs within six months after the HEES participation. The underlying probability of EE program participation is 4.9%. Prior EE program experience, on the other hand, only increased the probability by 1.4%.

The lower part of Table 4 models the probability of EE program participation within one whole year after the HEES program[4]. The underlying probability of EE program participation is 8.1%. The HEES program increased EE program participation by 4.1%, and prior EE program experience only increased the probability by 1.3%.

Comparing the upper part and the lower part of Table 4, the results are similar as in the SCE's case. The HEES program has higher impact as the analysis period includes longer time, but when comparing to the underlying probability of EE program participation, the effects were actually diminishing.

Table 5 below reports the key parameter estimation for the SCE SmartConnect My Account and Budget Assistant analysis. The BA_Participation and MA_Participation are the flags for households who participated in BA and/or MA, and it is possible that one household participated in both programs. The SV_Participation equals to one if the household had participated in SCE's survey program and had received energy saving kits like LED night light and water saving shower head[5]. The PriorEEPart is the indicator for households who had participated energy efficiency program before the MA and/or BA participation.

Table 5 shows that both MA and BA programs increased the customers' probability of participating in EE programs in the future. The effects are statistically significant. The survey program and prior EE program experience also increase the probability significantly.

[4] For the non-participants, this is the one whole year after the matching period.

[5] SCE gave away energy saving kits to most of the households that participated in the survey programs through on-site, telephone, mail-in, and long version of online survey. Households that participated in short version of online survey did not receive the kits. Therefore, not all the survey participants got flagged by SV_Participation. The energy saving kits include CFL(s), LED night light(s), faucet aerator, and waster saving shower head.

Same as for the HEES models, the upper part of Table 5 reports the results for EE program participation within six months of analysis period. During this period, BA program increased the probability of EE program participation by 0.43%, comparing to the underlying probability of 0.92%. MA program increased the probability by 1%, higher than the BA program. This is consistent with the MA and BA program contents. While MA showed account usages along with EE program information, BA only sent out account usage and alerts. Therefore, it is expected that the MA program would induce more EE program participation than the BA program.

Table 5. Key parameter estimates for the SCE SmartConnect my account and budget assistant programs

Variable	Estimate	StdErr	ProbChiSq	MarginalEffect
Dep Var=1 if participate in EE within 6 months				
Intercept	-5.4844	0.1087	<.0001	-0.0485
BA_Participation	0.3276	0.0352	<.0001	0.0043
MA_Participation	1.1404	0.0507	<.0001	0.0100
SV_Participation	2.3176	0.0417	<.0001	0.0669
PriorEEPart	1.4217	0.0558	<.0001	0.0260
Dep Var=1 if participate in EE within 12 months				
Intercept	-5.4741	0.0919	<.0001	-0.0674
BA_Participation	0.6162	0.0285	<.0001	0.0117
MA_Participation	1.4809	0.0442	<.0001	0.0195
SV_Participation	2.1186	0.0376	<.0001	0.0752
PriroEEPart	1.9028	0.0487	<.0001	0.0624

The survey program increased the EE program participation by 6.7%, much higher than the MA and/or BA programs. This also makes sense, because the survey program actively suggested the surveyed customers to participate in the EE programs, while MA and BA programs just passively showed the information online along with the other account information. Prior EE program experience increased the probability by 2.6%, higher than the MA and BA programs, but lower than the survey program.

When comparing this set of results with the SCE HEES program analysis results, it is obvious that the impacts from the survey and prior EE program participation are much higher than the MA/BA model. The difference may mainly due to different samples used. As shown in Table 1 and Table 2, the two samples' statistics are very different, and as explained in Section "Self-Selection Bias and Non-Participation Sample Selection", the two programs were different in both time period and geographic locations. Also, as pointed out, for the MA/BA sample, the non-participants were selected to match to the MA/BA participants, not the survey program participants, and the effect from the survey program might be overestimated.

Same as in case of HEES analysis, the marginal effects listed in the lower part of Table 5 are higher than the upper part ones. The underlying probability of energy efficiency program participation during one whole year in the analysis period is 1.3%. The BA program increased the probability by 1.2%, the MA program increased the probability by 2.0%, the survey program increased the probability by 7.5%, and the prior energy efficiency program 6.2%. It is also the same as in case of HEES programs that although the MA and BA programs' impacts are higher for the model including one whole year of analysis period, the programs exhibit a diminishing impact as time went by.

Conclusion and Further Analysis

The statewide HEES programs and the SCE SmartConnect MA and BA programs both significantly changed the customers' energy usage behaviors and reduced participants' energy bills. In the analysis, we found that both programs also increased the probability of future EE program participation, and the influence was statistically significant.

We also found that the magnitude of the impact was much higher in the HEES program than in the MA and/or BA program. The possible explanation might be that the audit program actively suggested that customer participate in EE programs, while the MA/BA programs just passively presented EE program information along with the energy use.

The data needed for both analyses includes 1) behavioral program tracking data, 2) EE program tracking data, and 3) weather data, which is the same as the data needed for the behavioral program evaluation. Therefore, this kind of study requires not much extra costs.

On the other hand, since the data used here is the EE program tracking data, the results should be interpreted with cautions. We could conclude that the behavioral programs increased the probability that the participants would adopt EE measures through EE programs, but could not generalize the results and say that the participants would have high probability to adopt EE measures outside EE programs. To approve the latter statement, surveys on both behavior program participants and none participants are needed.

References

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