Planners do it, implementers do it, even evaluators should do it: Utilizing segmentation to assess program performance

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ABSTRACT

As the energy efficiency industry shifts in terms of the types of measures offered, populations targeted, and strategies to achieve energy efficiency and conservation, now is the time to introduce new approaches that support both optimized program delivery and actionable evaluation results. Program implementers are increasingly moving towards segmentation, micro-targeting and behavior-based strategies to deliver nuanced programs that achieve energy savings across different groups of customers. This paper posits: why shouldn't evaluators do this as well?

As has been noted across the energy efficiency industry, traditional methods for calculating net-to-gross (e.g., a self-report method) are lacking, producing a relative and oftentimes imprecise measure of attribution for energy efficiency programs. In addition, these methods produce an aggregate number, despite the fact that we know customers vary in terms of their motivations, barriers and drivers to save energy. Moving towards segmentation is a way to optimize program delivery, as well as to enhance evaluation approaches. As implementers go, so can evaluators in terms of leveraging social science based tools to measure effectiveness of targeting efforts, as well as attribution.

In this paper, we introduce a novel approach to estimating the net effects of demand side management (DSM) programs that we call evaluation by segmentation (EBS). This method avoids the major issues that trouble the traditional self-report method of establishing a net-to-gross-ratio (NTGR), and therefore net effects, while providing program designers with the basis for developing program targeted recruitment strategies.

Introduction

Everyone has reservations about using self-report methods to estimate net effects. Yet we keep using it, usually exclusively, to do just that. We introduce Evaluation by Segmentation (EBS) as an alternative approach to strictly utilizing self-report methods for determining net effects. EBS works to avoid the most objectionable features of self-reported NTGRs and the most difficult aspects of comparison groups, while offering relevant context to inform program design and delivery.

Evaluation by Segmentation encompasses more than just evaluation, as we can also use it as a tool for program design. Segmentation and propensity scoring are becoming very popular in our field, but we often overlook the fact that there are more free riders in some segments than in others. It is only logical that people who are diligent about living as green as possible are more likely to adopt energy-efficient behaviors without incentive or prompting, compared to people who are not at all concerned about the environment. Those who have lower incomes may have a different rate of program participation or adoption of measures and behaviors than those with very high incomes and very high usage.

Our firm is using an approach that explicitly considers these variables to help program planners and implementers think strategically about their targeting and messaging; and for evaluators to assess net effects without relying solely on asking participants what they would have done if the program were not available.

This approach hinges on establishing a naturally-occurring rate of energy-efficient behaviors for each segment. The net effects of a program are the incremental rates of program participation or adoption of measures and behaviors (and resulting savings) that go beyond the naturally occurring rates.

If program planners understand their customer segments, their motivations, their barriers, and what their free-ridership would likely be, they can choose to focus on increasing energy-efficient behaviors in the high-free-ridership segments (thus possibly increasing gross savings). Alternatively, program planners can focus on the segments less likely to adopt energy efficiency behaviors with messaging appealing to them specifically, thus producing more net savings, even if the gross savings may be lower than in the high-free-ridership segments.

Approach

We know that customers vary in terms of their rate of program participation or adoption of measures and behaviors. We observe this when evaluating the myriad DSM programs and products offered across the country, whether we look at smart thermostat programs and participant free ridership (e.g., would those wealthy, suburbanites purchase their Nest without the rebate anyway?) (Patterson 2016) or behavior programs where new research suggests that over 40% of customers actually increase their energy consumption after receiving home energy reports (Wayland 2016).

Below, we discuss the way that EBS can establish a counterfactual (that supports measuring attribution without relying on self-reported NTGRs), as well as support program design that targets programs by segments to provide insights and context for evaluators regarding opportunities for program optimization.

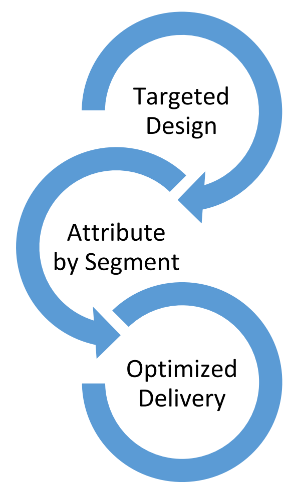

Figure 1. Framing the Approach

Developing a Framework

In this framework, the net effects of a program reflect the increase in purchase rates over and above the propensity to purchase for a given segment, multiplied by the average energy savings per purchase. The sum of those products across the segments is the net effect of the program. All other things being equal, if we establish the efficient equipment purchase propensities for each segment, and compare them to the actual program recruitment rate for each segment, we can calculate the net effect of the program for each segment, and therefore the whole program. To do so, we utilize three core steps: 1) establish the naturally occurring rates of program participation or adoption of measures and behaviors to segment customers, 2) apply propensity scores for net savings to estimate program impacts, and 3) refine program delivery. These steps all produce inputs that help to refine future program delivery. We outline these below.

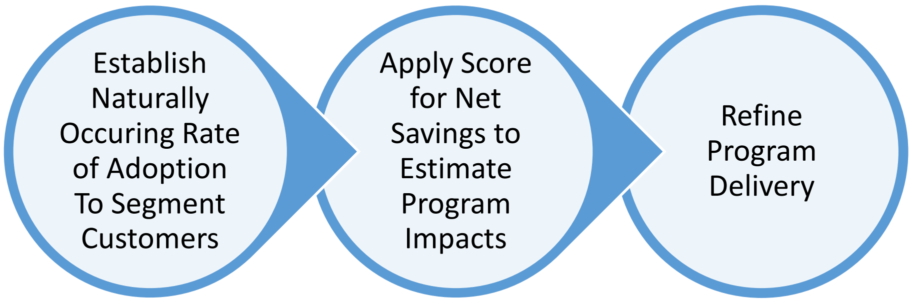

Figure 2. Evaluation by Segmentation Process

Establish Naturally Occurring Rate of Adoption to Segment Customers

We can establish a naturally occurring rate of purchasing equipment at a specified level of efficiency without program incentives or persuasion. This natural rate will differ by customer characteristics or segments, e.g. early adopters, green living, or thrifty shoppers, etc. Almost by definition, the naturally occurring rate of purchasing efficient equipment is the rate of free ridership that would accompany a program that offered financial incentives to purchase the same equipment. Therefore, a segment that has a high naturally occurring purchase rate for the program-incented equipment will contain a higher percentage of free riders. Thus, if segments are created in relation to naturally occurring rates of purchase of energy-efficient equipment, the naturally occurring rate will vary by segment.

The naturally occurring rate of program participation or adoption of measures and behaviors also reflects a customer's propensity to purchase, or the probability of taking action. In this step, we establish segments to ascertain the propensity to purchase energy-efficient equipment within each segment. The best approach to defining the segments is to use a method that ties the segment definitions to one or more target variables that connect to a program-relevant behavior, e.g. purchasing energy-efficient HVAC equipment, or other technology or behavior a program is working to promote.

This approach would guarantee that the segments were relevant to propensity to purchase energy-efficient equipment and could even incorporate the process by which propensities would be assigned to each segment (to be discussed later). As a result, we generate a "score" associated with each segment's propensity to purchase efficient equipment. In an impact evaluation, that score represents what will be the program's free ridership rate.

How do we generate segments and propensity scores? We can do this in multiple ways as outlined below:

- **Traditional Segmentation with a Target**: Classification and Regression Trees (CART)[1] generates segments specifically to predict a variable or concept of particular interest. This method forms segments based on the selection of variables and their values that increase the accuracy of predicting a target variable. For purposes of generating segments to use for EBS, we establish segments that predict the naturally-occurring rate of behaviors that program implementers are

[1] CART® is a software program that splits a sample into groups and subgroups that are made successively "purer" with respect to a target value on a variable of interest. In this case, it would be the propensity for an energy-efficient action.

promoting. The target variable in this case would be an item of data, or a composite of data items representing each person's history of purchasing energy-efficient appliances or at least intention to purchase them regardless of program offerings, and past program participation. The predictors would be traditional segmentation types of variables, or others that program planners and/or researchers would think appropriate to the program and target population.

- **Latent Class Discrete Choice Segmentation:** Latent Class Discrete Choice (LCDC) is a stated-preference method that uses specific products or programs as the targets of segmentation analyses. LCDC presents customers with a series of products (which can include programs) showing their attributes in bundles. From all of the choices the customer makes, we can determine the importance of each attribute, and the likely uptake rate of the targeted product (with or without incentives). LCDC allows separate choice patterns to emerge for different customer segments. Thus, segments and their different propensities to purchase energy-efficient products are a natural output of this method. These estimates are based on the stated preferences of IOU customers, not necessarily program participants. In addition, we can calculate anticipated NTGRs by using the associated simulator to generate expected rebated and non-rebated purchase rates. Thus, it is a good planning tool for considering various program configurations before launching any of them.

As described above, program planners can use a segmentation tool, such as LCDC, to generate segments that vary in their propensity to purchase program products with and without a rebate, based on stated preferences. This data collection and analysis can occur before, during, or after a program launch. However, we recommend conducting this type of segmentation prior to launch, for use as a planning tool to support rebate design and product promotion, as well as to establish each segment's propensity to purchase the product without the program.

Once we develop a segmentation scheme, we can incorporate those scores into a billing analysis or engineering analysis to estimate overall program savings. In many respects, this approach follows traditional forms of adjustments to gross energy impacts.

Applying the Framework: A Home Upgrade Program Example

To demonstrate this framework, we provide an example of a home upgrade program using an LCDC experiment with a sample of homeowners who have not yet participated in the program. Below we illustrate how to examine the choices customers make about home upgrades, establish naturally occurring rates of efficient upgrades, and create related segments. In this example, we conduct an LCDC experiment in the early stages of a home energy upgrade program.

Establish Naturally Occurring Rate of Adoption to Segment Customers

As part of an LCDC, we present a choice experiment to a random sample of homeowners, where the choices comprise several home upgrade scenarios that vary on important attributes for that activity. Attributes include project size, project cost, rebate size (including $0), getting a permit or not, variables representing degree of energy efficiency designed into the project, and others. We conduct a survey that asks customers about such things as past upgrades, attitudes, motivations, barriers, etc. We tie that information to other information we have about the customer including past participation in energy efficiency programs, energy usage, and type of home, etc. In Figure 1 below, we take proprietary work that we performed for a utility on the West Coast, and sanitized and simplified the numbers and attributes to illustrate the types of information we collected to establish a naturally-occurring rate for conducting efficient home upgrades.

Store 1 Block 1

Directions:

Please choose from among the following products, or specify "None of these" if you don't want any of them.
Circle the number corresponding to your choice.

Choice:	1	2	3	4	5
Program:	Regional	Regional	IOU	Regional	None of these
Upgrade type:	Efficient upgrade	None	None	Non-efficient upgrade	
Rebate %:	None	None	10%	30%	
Financing %:	None	50%	75%	50%	
Financing rate:	6%	4%	4%	4%	
Financing Channel:	Third party	Third party	IOU	Contractor	
Upgrade cost before rebate:	$20,000	$10,000	$15,000	$15,000	
Annual energy savings:	$4,000	$1,000	$3,000	$2,000	

Figure 3. Mock-Up of One "Store" in LCDC Questionnaire: Based on Home Upgrade Behavior

Once we complete the data collection, we model the data to estimate the importance of each attribute in predicting customer decisions as well as customer segments related to those decisions. To model attribute importance, we develop a simulator to test alternative program designs. The resulting coefficients represent the importance of each attribute. In Table 2, we provide a simulator where the upgrade "market" is represented by IOU program, regional programs, and non-program actions.

Table 1. Simulator for Home Upgrade Behavior

Product Marketplace	***Your product***				
Package name:	A	B	C	None	
Program:	IOU	Regional	None		
Upgrade type:	Efficient upgrade	Efficient upgrade	Efficient upgrade		
Rebate %:	20%	No rebate	No rebate		
Financing %:	50%	50%	No financing		
Financing rate:	4%	4%	No financing		
Channel:	Bank	Bank	Bank		
Upgrade cost before rebate:	$15,000	$15,000	$15,000		
Annual energy savings:	$3,000	$3,000	$3,000		
Adjustment factor:					
Probability of taking action	**17.0%**	**10.0%**	**5.0%**	**68.0%**	

The final row in Table 2 represents the estimated rate of program participation or adoption of measures and behaviors for each alternative path to an upgrade. The percentages (rates) add up to 100%, demonstrating the importance of representing the major (and sometimes minor) alternatives in the simulator output. We have shown 4 potential product bundles in this example (3 upgrade choices plus a non-upgrade case), but we can design the simulation to represent more or fewer products based on our knowledge of the market alternatives (and, in our actual work, we incorporated more examples).

As part of this simulation, we incorporate different configurations of upgrades by changing the attribute levels to represent the IOU program, including mean rebate amounts, mean efficiency levels, and any other program features to produce uptake rates for the program configuration, and setting those values to 0 or the equivalent non-program values. The latter would be the naturally occurring rate of upgrades that would be the equivalent of program values, but without the program. In other words, the rate at which customers would perform an upgrade that would mirror the program actions, performed outside of the program.

This analysis also produces segment descriptors, as well as allows us to focus on any one or combination of segments to capture rate of adoption of measures and behaviors for each major upgrade path. As a result, the program planner will know the estimated program participation rate of a given program design for each segment as well as what the rate of adoption of measures and behaviors of the same behavior would be without the program for each segment. As described before, this information allows the program planner to form a targeting and messaging strategy to promote the program, tailored to specific segments. The goal is to increase the (net) increment in program uptake for the targeted segment(s). Nominally, the difference between the propensity with and without the program would constitute the net effect of the program.[2]

Estimate Program Impacts & Apply Score for Net Savings

As described in the example above, we produce projected rates of customers taking home upgrade actions with and without the program, and will generate segments that relate to those decisions. We can then develop rates of adoption of measures and behaviors with and without the program by segment. After the program cycle is completed, or after it has run long enough to warrant an impact evaluation, we field a second survey (not an LCDC experiment) to determine actual rate of adoption of measures and behaviors with and without the program. To get maximum usefulness from this approach, the program team would strategically choose one or more segments as the target of tailored messaging. Table 3 illustrates outcomes (again, sanitized) from these two stages of planning and evaluation.

Table 2 LCDC Estimates of Projected & Actual Action Rates for Home Upgrade Program

	Estimates	Segment			
		Green-Mod Income	Green-High Income	Green-Low Income	Brown-Thrifty
1	Projected rate of taking action w/o program	2%	5%	0%	0.5%
2	Projected rate of taking action with program	10%	7%	0%	1%
3	Actual rate of taking action w/o program	5%	6%	0%	0.75%
4	Actual rate of taking action w/program	12%	8%	0%	1.50%

The first three of the four segments shown comprise customers with "green" attitudes and behaviors, but differ in their income levels—a factor that is quite important for home upgrade programs, given their expense. In the final column is a segment of customers who are not focused on the environment, but are thrifty in their habits.

For each segment, the table shows the rates at which customers in each segment indicate they would take energy-related home upgrade actions without program intervention (Row 1), representing the naturally occurring rate of this behavior, and that we also call the propensity to take this action. In this example, the highest naturally-occurring rate of 5% is found in the Green-High Income segment, and the second highest (2%) is in the Green-Moderate Income group. Low-income customers who are motivated by the environment are not likely to take this kind of action naturally because they are unlikely to be able to afford it. As you can see, the Brown-Thrifty segment yields a much lower program participation rate.

The second row of Table 1 shows the projected rate of taking home energy upgrade actions through the program. The difference between Row 1 and Row 2 shows the anticipated net effect of the program in each segment (recall that these numbers come directly from the survey we fielded before the program year). With this information, the program team may select a segment such as the Green-Moderate Income customers and seek to emphasize both the environmental benefits of a home energy upgrade and the availability of financing. Because of that focus, the anticipated 10% program participation

[2] To calculate the net savings for the program, the rate of program participation or adoption of measures and behaviors increase would be weighted by the savings associated with the average project.

rate might be raised to 12% (Row 4) due to an effective marketing campaign. This would mean that the net effect of the program would be 10 percentage points rather than the anticipated 8 points weighted by the average savings of the upgrades.

An aspect of the information in Table 1 that we should not overlook is the rates of completing home upgrades outside the program. This behavior will certainly take place by do-it-yourselfers or by contractors doing the work with and sometimes without a permit. We know from a California process evaluation of a home upgrade program that some contractors were selling against the program, using the argument that they could do the same work for less, but without the bureaucratic hassle of the program. If this work increased the energy efficiency of the home, these cases are considered as spillover. There is a naturally occurring rate of completing this work (shown as 2% in the table), but the program may well increase actions taken outside the program resulting from the program.

Consumption Analysis Application

The following equation provides an example of how we would apply a propensity score to an impact evaluation when using a consumption analysis. In this case, the non-program-influenced uptake rates in Equation 1 are applied to participants only. This approach is analogous to SAE models where engineering priors are entered into the dataset in place of dummy variables for participation. However, when segment propensities are entered, the resulting estimate is of net savings, rather than a gross savings realization rate, and would be interpreted as net program effects. The result incorporates both increases in uptake due to the program (compared to starting propensities) and how much energy is used and saved post program.

Savings statistically explained by this score would not "count" as program net savings. Only savings achieved by program participants beyond that predicted by their segment membership would be counted as net impacts. It is simple to represent this in an equation applied to a population of participants:

Equation 1

$$Usage_{it} = \alpha + \sum_s \beta_1 SegProp_{is} + \beta_2 Post_{it} + \beta_3 Post_{it} * SegProp_i + \beta_{it1-k} X_{it1-k}$$

Where:
$Usage_{it}$ =Kwh or therms for customer i at time t
$SegProp_i$ =Segment propensity for customer i
$Post_{it}$ =Pre- or Post-Period for customer i at time t
X_{it1-k} =Vector of covariates for weather, economic conditions, or others for customer i at time t
β_1 =Effect of free riders on usage
β_2 =Net effect of program
β_{it1-k} =Effects of covariates 1 through k for customer I at time t
α =Constant

β_2 will capture the extent that customers in high-propensity segments participate beyond their expected levels and save energy beyond what their propensity predicts, e.g., it will capture the change in usage beyond what is predicted by the segment propensity. Note that this estimate would capture both program participation rates as well as any behavior associated with *using* the new equipment as well. If analysts wished to capture only the increase in program participation rates, beyond those predicted by the propensity score, logit models can be employed with a similar specification.

Limitations

Despite the aforementioned benefits of EBS, including helping to establish better counterfactuals for elucidating attribution for net savings as well as supporting design and program delivery enhancements through actionable results, there are a set of limitations associated with this approach.

Developing Appropriate Propensity Scores

First, it is important to remember that assigning a propensity score to a segment does not imply that every person in that segment will take the action. So, assuming 100% of all persons in a high-propensity segment will take the action studied is not required to use the propensity as a naturally occurring rate of the behavior. In addition, some customers who do not expect to choose the energy-efficient measure might actually do so. As a result, the customers switching from not intending to purchase energy-efficient measures to actually purchasing them could counteract the customers who switch in the other direction. It is possible, therefore, that the propensity scores are not biased either way. However, we cannot assume that this is the case, rather a researcher may want to establish the validity of this measure of propensity or naturally occurring rate of purchasing the energy-efficient product.

Other industries, such as transportation and consumer electronics, and numerous others have profitably used the stated-preference discrete choice method for planning and policy. The method was the basis for planning the San Francisco Bay Area public Transit system (BART) and was found to be highly accurate in its predictions. It was, in fact, the basis for Daniel McFadden being awarded the Nobel Prize, and constituted the content of his Nobel lecture. However, since our industry has typically not used the stated-preference discrete choice method to assess the net impacts of programs, we should not assume that the level of accuracy achieved in other industries will be sufficient for energy efficiency programs. Importantly, any efforts should allow for adjustments to the measured intentions of customers, by using a feature of the simulator to insert an adjustment factor that reflects the difference between intention and behavior. As discussed earlier, there could be customers who overstate their intentions and others who might understate them. So, if the net difference between stated intentions and behavior is that only 70% of stated intentions translate to behavior, we can adjust relevant rates by 0.7. We can develop adjustment factors through surveys specifically designed to estimate the differences between intentions and behavior, and we can use revealed-preference information of various kinds as a basis for adjustment factors. We have used sales data, for instance, to create adjustment factors to ground stated preferences in reality.

Literature also suggests alternative approaches to calibrating stated preferences to revealed preferences (Adamowicz et al. 1997; Earnhart 2001; Paradiso and Trisorio 2001; Little and Berrens 2004; Whitehead et al. 2008; Chang, Lusk, and Norwood 2009; Moser, Raffaelli, and Notaro 2013). The best method to use depends on the type of decisions represented in the study, and the nature of the alternatives available to customers that is the basis of the stated and revealed preferences. When revealed preferences were determined, some alternatives may not have been available to consumers. This causes complexities in using stated and revealed preferences together.

In any case, the accuracy of the predictions made by stated preference studies is related to the quality of the study design. It is essential that the sets of choices that customers are asked to respond to reflect accurately the market alternatives for that product. It is also essential that all of the important attributes of that product that are available, or will/can be available, are represented in the study.

Further, additional value associated with propensity scores is the *relative* propensities across the segments, or how much more likely are customers in one segment to choose energy efficiency without the program versus those in another segment? Well-developed segments will identify those with the highest and lowest propensities (and those in between), and should align directionally with the segmentation results (e.g., should move in the same direction). As a result, the relative success of programs recruiting within selected segments should be well represented by how much the recruitment and savings rates exceeded the predicted propensities.

Considering External Factors

The behavior and intentions of any segment may be different in some situations than others, and this difference may be accentuated by the measure type and end use of the efficient measure. Even customers with environmental attitudes will usually require more motivational sources than the environment. We found this in the evaluation of the whole house program in California where highly environmentally concerned customers, after expressing interest in the program, began to drop out as they went further in their potential participation. It was only the customers with both environmental and comfort concerns that tended to complete the program. Also operating was the level of financial resources available to them. On the other hand, another study evaluating a very similar program in Vermont (Research Into Action 2012), found that the customers who completed the program were the customers that had the highest mean scores on concern for the environment. We hypothesized that the difference between the "green" customers in Vermont versus California is not the customers but the climate (context). In both programs, gas savings drove the overall program savings, implying that the winter weather was the driving force. It is colder in Vermont than it is in northern California, and easterners generally have higher heating costs than Californians (another element of context); thus it may be that the return on investment from doing energy efficiency upgrades to their homes (due to technology and end use) is considerably better in Vermont than California. In this situation, the Vermonters also experienced a combination of altruistic (environmental) and self-interest (cost savings) motivations, so the environmentally-concerned tended to go all the way to full participation.

The examples just described illustrate several points. HVAC measures, including furnaces, heat pumps, weatherization, fenestration, air sealing, etc., are expensive measures, requiring much more financial commitment than many other measures that households can take to reduce energy use. This fact eliminates many households who just cannot afford to undertake this kind of upgrade, so only customers with relatively high incomes have the ability to conduct upgrades. Customers with more moderate incomes, while interested in preserving the environment, may not realize how expensive these measures are until they begin the upgrade process. However, if the monthly savings on winter energy bills is very noticeable, the first-cost shock may be overcome by the prospect of substantially lower energy bills. Thus, the combination of end use, measures, climate, and energy costs come into the decision to mount a major home upgrade to save energy. In other words, propensities to take energy-saving action may be different even among "green" customers (or any other segment) and will depend, in part, on these factors.

Of course, other contextual factors may have influence as well, including the demographics and the economy of the area served by a program. All of this means that it is important to take these factors into account when generating and interpreting propensities, and using them to represent naturally occurring rates of energy efficiency actions. They are also central to decisions about sampling. When variations are anticipated by climate, technology, end use, and other factors, those variables will have to be represented adequately in sampling such that separate propensities or adjustments can be delivered.

Using Stated Preferences as a Counterfactual

Readers may consider the fact that the LCDC method of establishing a counterfactual is, at base, a self-report method, and we have suggested that our approach avoids the issues surrounding the self-report method. Our argument is that the stated-preference discrete choice method tends to camouflage the socially-desirable responses, which is the source of much of the self-report method critique. Often the energy-efficient product that appears as one choice among several, is paired with other attributes that may overwhelm the efficiency attribute. Thus, the socially-desirable attribute appears in multiple options and sets of options, making it much less likely that the respondent would choose an option just because it is socially desirable. In a traditional self-report set of questions, it is clear that saying they would have selected the energy-efficient option regardless of the program paints the participant in a good light. This is much less likely in a discrete choice exercise.

Conclusion

This paper proposes an alternative approach to evaluating energy efficiency programs, which seeks to tie estimates of net program impacts to the naturally occurring rate of program-promoted behaviors, by segment. Our emphasis in this paper is on using customer segments to help with establishing naturally occurring rates of behaviors (purchase and otherwise) as well as for creating strategic targeting and messaging by segment.

The approach is not based on the traditional self-report approach. Although the LCDC approach *does* rely on self-report, as it is based on a survey asking customers what they would choose among several options (including 'none of the above'), the difference is that what is being reported by the customer is not whether the program influenced them, nor about a hypothetical alternative to decisions made in the past. Rather, what this approach provides, is a way to avoid these known difficulties, limiting the chances of social desirability bias or self-interest bias in terms of attribution results. This is because what would be considered the socially desirable response and/or the self-interest response is masked by the nature of the experiment and the context in which the choices are made. Our firm is currently applying this approach to generating customer segments using LCDC and testing this approach as part of ongoing efforts.

In addition to estimating the naturally occurring rates of promoted behaviors and developing segments relevant to those rates, EBS results can support a wide range of stakeholders in their decision making.

- Program planners can use these findings to have more certainty in terms of how attribution will be calculated. Specifically, program administrators will know the differences in naturally occurring rates of relevant behavior, and likely NTGRs, in advance of program launch. This gives the planner the knowledge to make decisions about where to target customized messaging to maximize net savings.
- Program implementers can use these findings to focus on the program, rather than worrying about participation rates as well as decide whether their best strategy would be to recruit among high-propensity (e.g. green) customers to get high gross impact but possibly low net impact, or whether to recruit among less motivated customers and get more net impact per recruit. In addition to producing net savings associated by segment, this effort will also support program managers in terms of making strategic decisions about where to focus their recruitment efforts, and manage free ridership rates to achieve overall program and portfolio goals.
- Regulators can use these findings to enhance certainty around determining attribution, providing a consistent and fair roadmap for driving policy choices and program offerings.
- And, finally, evaluators can use these findings to help scope attribution into planning and process results, providing actionable insights rather than punitive scores to their clients.

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