SESSION 2D

MEASURING BEHAVIORAL IMPACTS: THE STRUGGLE FOR CONTROL

Moderator: Patricia Gonzales, NYSERDA

PAPERS:

I can't use a Randomized Controlled Trial – NOW WHAT? Comparison of Methods for Assessing Impacts from Opt-In Behavioral Programs

Bethany Glinsmann, Navigant Consulting
Bill Provencher, Navigant Consulting & University of Wisconsin-Madison

Some Insights on Matching Methods in Estimating Energy Savings for an Opt-In, Behavioral-Based Energy Efficiency Program

Bill Provencher, Navigant Consulting & University of Wisconsin-Madison
Bethany Vittetoe-Glinsmann, Navigant Consulting
Anne Dougherty, Opinion Dynamics Corporation
Katherine Randazzo, Opinion Dynamics Corporation
Phil Moffitt, Cape Light Compact
Ralph Prahl, Prahl and Associates

Control Group Wars - There's More Than One Way to Win the Battle

Dave Hanna, Itron, Inc.,
Kelly Marrin, EnerNOC, Inc.

SESSION SUMMARY:

Randomized Controlled Trials (RCTs) are the gold standard for evaluation; however, many energy efficiency programs are designed as opt-in programs, making a control group impractical or impossible. This session will focus on different approaches for estimating the impacts from behavioral programs using various types of control group methods. A comparison of these control group methods, including advantages and disadvantages of each, will be explored.

The first paper introduced by Glinsmann and Provencher compares different approaches for estimating the impacts from an opt-in behavioral program. Three model specifications are developed and potential sources of bias from each method are discussed. All three model specifications were applied to help triangulate the estimated impacts and potential for self-selection bias. In this particular application, each model produced relatively similar results, indicating that the results likely do not suffer from self-selection bias. However, control of self-selection bias may not always be the case and therefore future evaluations of opt-in programs that lack a control group should estimate multiple model specifications to better understand the potential for self-selection bias inherent in the program results.

The second paper by Provencher et al. examines two statistical models in which participants in an opt-in behavioral program are matched to non-participants based on historical energy use to estimate program savings. The first model involves standard regression analysis, while the second uses regression analysis to modify a matching estimator. The extent to which matching on energy use is likely to address two potential sources of bias in estimating savings from the program: (a) specification bias arising when a regression model of energy use is misspecified; and (b) selection bias arising if participants are different than non-participants in ways that affect energy use and are not observable in the available data are discussed. The application is to a cohort of customers participating in a small-scale opt-in residential behavioral program in eastern Massachusetts. The two models generate similar estimates of program savings; the first estimates that average household savings in the first year of the program were 1.49%, and the second estimates that average savings were 1.36%. Estimated savings are statistically significant despite a small sample size and low savings, likely reflecting the high quality of the matches. A further pseudo-test indicates the estimates are not affected by selection bias.

The third paper by Hanna and Marrin describes two control group selection techniques, Stratified Propensity Score Matching (SPSM) and Stratified Euclidian Distance Matching (SEDM), used to evaluate two Advanced Meter Infrastructure (AMI) enabled information feedback programs. Both evaluations employed a non-equivalent control group design which is structured similar to a pre-post randomized design (i.e., Randomized Control Trial) but lack the important quality of randomization. Because the control groups are not randomly selected, they can never completely eliminate self selection bias. However, they can be developed to control for bias from observable factors that influence energy usage and potentially savings. The authors recommend that when using either of these control group matching methods: a) the ratio of non-participants to participants should be at least 4:1, b) when the non-participant population is extremely large (greater than 10 times the participant population), first randomly select a smaller non-participant population for use in the matching process, c) when the same control is the closest to two different treatment customers, calculate the second closest for all treatments and minimize the total overall distance between treatments and controls, and d) use selection with replacement when the ratio of non-participants to participants is less than 4:1.