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The problems and solutions of predicting participation in energy efficiency programs

Alexander L. Davis *, Tamar Krishnamurti

Department of Engineering and Public Policy, Carnegie Mellon University, 5000 Forbes Ave., Pittsburgh, PA 15213, United States

HIGHLIGHTS

- Energy efficiency pilot studies suffer from severe volunteer bias.
- We formulate an approach for accommodating volunteer bias.
- A short questionnaire and classification trees can control for the bias.

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ABSTRACT

This paper discusses volunteer bias in residential energy efficiency studies. We briefly evaluate the bias in existing studies. We then show how volunteer bias can be corrected when not avoidable, using an on-line study of intentions to enroll in an in-home display trial as an example. We found that the best predictor of intentions to enroll was expected benefit from the in-home display. Constraints on participation, such as time in the home and trust in scientists, were also associated with enrollment intentions. Using Breiman's classification tree algorithm we found that the best model of intentions to enroll contained only five variables: expected enjoyment of the program, presence in the home during morning hours, trust (in friends and in scientists), and perceived ability to handle unexpected problems. These results suggest that a short questionnaire, that takes at most 1 min to complete, would allow better control of volunteer bias than a more extensive questionnaire. This paper should allow researchers who employ field studies involving human behavior to be better equipped to address volunteer bias.

1. Introduction

The past 6 years has seen rapid growth in legislation and research on the "smart grid" in the United States. Title XIII of the U.S. Energy Independence and Security Act of 2007 (U.S. Public Law 110-140) and Title IV of the American Recovery and Reinvestment Act of 2009 (U.S. Public Law 111-5) made resources available for modernizing the electric power grid. A critical component of these laws promotes better understanding and management of electricity use among residential customers. US electric utilities are conducting studies that test programs to achieve these goals, including tariffs such as critical peak pricing, home automation technologies such as smart thermostats, and feedback approaches such as in-home displays. These studies are designed to rigorously test these programs to ensure sound conclusions, even if that rigor is costly.

The most significant barrier to the validity of these studies is volunteer bias, where a customer's decision to be in the study may be causally related to benefit in the study. This bias can occur whenever someone offered the program refuses to participate, as refusal may indicate that the person would not have benefited from the program. As a result, using an all-volunteer sample is likely to overestimate program benefits to the population from which the sample was drawn.

Consider an extreme example that illustrates the problem. Suppose that residential customers choose to participate in an energy efficiency study based only on accurate knowledge about whether they will benefit [1]. If this is true, the study sample will be comprised wholly of customers that will benefit, whereas no person outside of the study would benefit. A failure to understand this would lead researchers to incorrectly conclude that the program would greatly benefit the general population when they would actually not benefit at all. That is, volunteer bias is an especially severe problem if researchers are unaware of the difference between volunteers and non-volunteers, or if aware, unable to compensate for it.

Recruiting a representative sample with little or no volunteer bias is not easy. Some customers do not want to participate no

* Corresponding author. Address: Department of Engineering and Public Policy, Center for Climate and Energy Decision-Making, Carnegie Mellon University, 5000 Forbes Ave., Pittsburgh, PA 15213, United States. Tel.: +1 412 216 2040.
E-mail address: alexander.l.davis1@gmail.com (A.L. Davis).

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matter how much they are incentivized or cajoled, and it is difficult to determine their reasons for refusing. Unless these reasons are identified and taken into account when estimating the benefit of the program, inferences from the sample to population are not warranted. Comparing the sample and population on some observable characteristics is not sufficient to reduce the problem [2], as observed characteristics may not capture the causes of both volunteering and benefit in the program.

Despite this challenge, recruiting a representative sample is a necessary condition for establishing the validity of an energy efficiency study involving residential customers. It is a critical ''part of the science'' of any research involving human behavior [3]. In this paper we discuss the evidence on the causes of volunteer bias in energy efficiency programs and present a method of accommodating bias when, despite best efforts, it does occur [4]. Our approach is comprised of two parts. First, we develop a simple questionnaire that can be used to predict who will volunteer in an energy efficiency trial of in-home displays. We derive questionnaire items from previous research on volunteering [5] and evaluate their psychometric properties [6–9]. Second, we develop statistical models based on this questionnaire that accurately predict intentions to enroll in an in-home display trial. To test the quality of these statistical models, we compare modern machine learning algorithms against a simpler, often better, performing alternative: the best predictor [10,11].

2. Prevalence of volunteer bias

In this section we review the history of volunteer bias in residential energy efficiency studies in North America, using in-home displays as an example.[1] Volunteer bias in these studies has predominantly occurred in two ways. In the first way, customers self-select into the study and are then randomly assigned to different treatment groups. This makes inferences from sample to population uncertain because any factor that causes both volunteering and benefit cannot be controlled.

As an example of the first type of volunteer bias, the BC Hydro PowerCost Monitor time-of-use pilot used single family dwellings in British Columbia with an opt-in design [13]. Those recruited were more educated, had higher annual household income, were more knowledgeable about electricity conservation, more active in trying to save energy, more willing to change habits, and used on average 1700 kW h less than other comparable homes in the BC area. This study fits into the first volunteer bias category because random assignment to the treatment group (a PowerCost Monitor) or control group (no PowerCost Monitor) occurred *after* participants opted into the study. Because of volunteer bias, this design does not allow one to extrapolate from the study sample to the population. Both observed (e.g., household income) and unobserved differences between the sample and the population could make the study's results not applicable to the population. However, because random assignment occurred after volunteering decisions were made, the study does allow valid comparisons between groups in the sample.

A second type of volunteer bias, where studies recruit the control and treatment groups differently, not only makes inferences from sample to population invalid, but also invalidates any comparisons between groups within the sample. Because customers recruited for the control and treatment groups may be different in unknown ways, such studies cannot separate the effectiveness of the treatment (e.g., the in-home display) from differences between how samples were obtained.

Almost every trial of in-home displays succumbs to the second, more severe, form of volunteer bias. For example, the Milton Hydro Direct Energy Smart Home Energy Conservation Kit study recruited participants using telephone, direct mail, and billing inserts [14]. Those eligible to receive an in-home display had to be at least 18 years old, must have lived in the home for at least one year, did not plan to move, and expressed a willingness to complete two surveys during the study. Eligible customers who expressed interest and registered on-line were then contacted for an installation appointment based on the order they registered, resulting in 108 homes having an in-home display installed for free.

The control group was recruited differently, consisting of 23 volunteers from a pool of 300 recruited customers who had homes that were judged to be of similar size and age to that in the treatment group, who completed a survey for a $100 gift certificate, and who lived in geographic clusters near the treatment group homes. Any factor that differed in the recruitment approach, for example the use of the gift certificate, could make the control group not comparable to the treatment group. This pattern of recruiting those in the treatment and control groups differently holds for almost every other trial of in-home displays, including the Oberlin TED5000 study [15], the Ontario Energy Board Hydro One pilot [16], the Energy Trust of Oregon PowerCost Monitor study [17], the Baltimore Gas and Electric Smart Energy Pricing Pilot with the Energy Orb [18], the Omaha Public Power study [19], and the Florida Power and Light Energy Detective study [20].

Not all studies of in-home displays, however, have been affected by volunteer bias. The first exception, the Polk's Landing study [21], had displays installed in homes before customers bought them, with no way for buyers to know which homes had the displays beforehand. The Southern California Edison study [22] used an opt-out design with an opaque opt-out procedure, resulting in no opt-outs. The Commonwealth Edison Energy Smart Pricing Pilot with Pricelight study [23,24] and PG&E's Smart-Rate Pilot [25] both explicitly modeled volunteer bias using a propensity score model, an approach that is discussed in Section 3. Lastly, studies of energy efficiency program adoption by commercial entities, such as utilities, have shown that volunteer bias is minimal [26].

3. Adjusting for volunteer bias

Even if one follows current best practices for recruitment [27–29], some proportion of those who are offered the program will not participate. Fortunately, if a statistical model can be created that accurately predicts who volunteers and who does not, then the risk of incorrect generalization from sample to population can be minimized.

One simple approach is to use *propensity score adjustment* [30,31], that explicitly models the probability of volunteering for each person offered the program. While the justification for this approach is technically sophisticated, the intuition behind it is simple: if one can accurately model the probability of each customer volunteering for the program, then by adjusting for this probability (or propensity), one can generalize from the sample to the population.

The propensity score approach was used in both PG&E's Smart-Rate Pilot [25] and the Commonwealth Edison Energy Smart Pricing Pilot [23,24]. The Commonwealth Edison propensity score model, for example, included whether customers purchased new major appliances, used a fan to reduce costs, lived in a single-family detached home, were above 65 years old, and the number and type of people living in the household. Using logistic regression, they found that those who used fans to reduce costs, as well as

[1] This does not merely apply to in-home display studies, but we focus on them here to keep the discussion shorter. Davis et al. [12] provide additional references to studies on dynamic pricing and home automation.