**[*USING TARGETING TO OPTIMIZE PROGRAM DESIGN: EVIDENCE FROM AN ENERGY CONSERVATION EXPERIMENT*]**

[Muxi Yang, Cornell University, my458@cornell.edu]

[Todd Gerarden, Cornell University, gerarden@cornell.edu]

## Overview

The central goal of program evaluation is to identify and design interventions that maximize welfare criteria. A vast literature of prior work focuses on identifying programs that generate positive net benefits. Recent methodological advances present a new opportunity to optimize the design of programs to maximize those net benefits. In particular, recent work on treatment assignment policies – rules that govern which individuals should be treated and which should not – provides a theoretical foundation and a framework for maximizing the expected benefits of interventions in the presence of treatment effect heterogeneity. These methods have the potential to generate large welfare gains in many domains. In this study, we apply the Empirical Welfare Maximization (EWM) method to derive treatment rules that maximize the expected benefits of home energy reports, a large-scale behavioral intervention to encourage energy conservation. In this program, personalized letters with feedback and social comparisons on energy consumption are mailed to residential households to address imperfect information and behavioral biases. Homeenergy reports (HERs) have been adopted widely by utilities across the United States, reaching at least 6.2 million households (Allcott and Rogers, 2014). Considering the high stakes – an estimated annual cost of 1.2 billion dollars if scaled nationally– it isimportant to design these programs to maximize their net benefits. Home energy reports have been widely implemented as randomized controlled trials (RCTs). The use of RCTs has been integral in establishing the causal short- and long-term impacts of HERs on energy consumption (see, for example, Allcott, 2011; Brandon et al., 2019). However, repeated randomized trials are unlikely to be welfare maximizing given previous findings of heterogeneous treatment effects, which could be driven by heterogeneity in both households preferences and energy market distortions, among other things (Costa and Kahn, 2013; Allcott et al., 2015; Myers and Souza, 2018). For example, prior work has found that certain households could increase electricity consumption after receiving positive feedback in HER letters (Schultz et al., 2007; Byrneet al., 2018). Due to this potential adverse response, and given that HER programs incur implementation costs, it could be welfare-enhancing to utilize information from prior RCTs to identify and target households that "should be" treated based on observable characteristics.

## Methods

Leveraging data on household-level monthly electricity consumption, treatment status, and five demographics characteristics from an HER program with over 390,000 participants, we apply new statistical learning methods to identify treatment assignment rules that maximize the program’s net benefits.We motivate our analysis of the gains from targeting by providing evidence of heterogeneous treatment effects. We estimate parametric triple-difference regressions that provide suggestive evidence of how treatment effects vary for households above and below the median of four observable household characteristics: pre-treatment electricity consumption, income, building size, and house age. Households with high pre-treatment consumption reduce electricity usage more than households with low pre-treatment consumption. A similar pattern emerges for income. There is relatively less heterogeneity in treatment effects in terms of building size and house age. Households with larger and older homes appear to exhibit slightly larger treatment effects but the differences with those of smaller and newer houses are not statistically significant. We use this suggestive evidence on heterogeneous treatment effects to guide the selection of covariates for our targeting analysis.In our main analysis, we search for simple and transparent treatment rules that maximize the net benefits of the intervention. To do this, we restrict our attention to twohousehold characteristics at a time – for example, pre-treatment consumption and income– and search over two classes of treatment rules. First, we search over quadrant partitionsof each two-dimensional characteristic space to identify the quadrant that, when treated, maximizes expected benefits. Second, we use a linear rule with cubic terms to allow for a more flexible partitioning of the characteristic space. In both cases, we search for rules using three separate criteria: expected energy conservation, expected private costsavings, and expected social cost savings. For the cost savings analyses, we account for both the value of electricity conserved and the cost of administering the program. The result is a rule that determines treatment based on any combination of two household characteristics that is easy to implement and can be visualized in two dimensions.

Our empirical strategy, the EWM method, is a recently developed statistical learning method in the growing literature on optimal treatment assignment. The learned treatment policies are "optimal" in the sense that they achieve minimax optimal rates of convergence for utilitarian regret, or the utility loss from failing to adopt the ideal rule (Manski, 2004, 2009; Imai et al., 2013; Hirano and Porter, 2009; Stoye, 2009). Using this criteria, the problem can be considered in two separate cases. First, when thereis no constraint on the treatment policy class and the estimator of conditional averagetreatment effects (CATEs) for each individual achieves the minimum regret bound, the optimal policy is to treat all individuals with the desired sign of treatment effects (Hiranoand Porter, 2009). However, to our knowledge, the regret-optimal estimator for CATEs in the unconstrained case has yet to been shown. Stoye (2009) shows that in the complex setting where covariates are continuous and policies have no functional form constraints, minimax-regret optimally can’t be achieved. Alternatively, treatment policies can bederived in a simpler setting where the policy class is constrained and non-complex. In this case, it is possible to achieve the optimal regret bound even if CATE estimation itself is not guaranteed to be regret-optimal (Kitagawa and Tetenov, 2018; Athey and Wager,2021). In particular, Kitagawa and Tetenov (2018) show that given exogenous binary treatment with known propensity scores, the constrained treatment policy that maximizes empirical welfare achieves the optimal regret bound.

In a closely related literature on heterogeneous treatment effects, Wager and Athey(2018) established the asymptotic normality of honest causal forests and the theoretical basis for causal inference using this approach. In this line of research, the goal is to minimize squared-error loss instead of utilitarian regret (Athey and Wager, 2021). Allcott and Kessler (2019) and Knittel and Stolper (2019) derived unconstrained treatment rules for HERs based on the sign of estimated CATEs using machine learning approaches such as causal forests, gradient forests, and elastic nets. Compared with unconstrained treatmentrules, the EWM rules are more transparent and easier to implement. This is appealing especially in this context where the gain from more complex treatment assignment rules based on observable characteristics may be modest relative to simple treatment rules, as pre-treatment consumption is found to be a dominant factor for targeting. In addition,the EWM method can explicitly accommodate additional constraints in settings where key targeting dimensions need to be pre-determined or constrained. Finally, our use of the EWM method integrates the decision problem and statistical inference. By solving forthe treatment rule that explicitly maximizes the sample analog of the welfare criterion, learning the treatment rule and conducting inference on the associated welfare gain is an integrated process.

## Results

We find large gains in cost-effectiveness from using observable household characteristics to target treatment. Our central estimate suggests the predicted reduction inelectricity consumption from targeted treatment assignment roughly doubles the consumption reduction from the randomized treatment assignment in the actual RCT. When targeting to maximize cost savings rather than energy conservation, the learned optimal treatment assignments achieve $0.65 - $0.82 in private cost savings per household per month, net of HER implementation costs, or roughly $385,000 - $485,000 of total net cost reductions per year for the sample. By contrast, we estimate that the RCT generated net cost reductions of $50,000, implying that targeting increases the net savings by an order of magnitude. To our knowledge, this is one of the first studies that directly derives optimal treatment assignments for an energy information provision program. Our results confirm the potential of targeting treatment and demonstrate an early application of statistical learning methods to derive optimal treatment rules in policy classes with explicit constraints, which is often necessary in practical settings. The results could be used to propose easily implemented treatment rules to improve the cost-effectiveness of energy conservation programs.

## Conclusions

This paper investigates the potential for targeted treatment rules to improve the net benefits from a large-scale behavioral intervention to encourage energy conservation. We empirically verify that providing personalized feedback on energy usage and social comparisons with efficient neighbors causes a reduction in energy consumption, and that this effect is most pronounced for households with high pre-treatment electricity consumption. Exploiting this heterogeneity in treatment effects, we derive simple and transparent treatment rules based on observable household characteristics that produce significant gains in net cost savings relative to no treatment. Our central estimate suggests the predicted reduction in electricity consumption from targeted treatment assignment roughly doubles the consumption reduction from the randomized treatment assignmentin the actual RCT. When minimizing costs, the optimal treatment assignments achieve roughly $385,000 - $485,000 of total cost reductions per year for the sample (net of program implementation costs). By contrast, we estimate that the RCT generated net costreductions of $50,000. Adopting machine learning models for causal inference is receiving growing attention from economists. We apply a method grounded in statistical learning theory and empirically investigate its performance in deriving treatment rules under an ideal setting for simple, transparent policy classes. The treatment rules we derive are transparent and easy to implement. Our results have clear policy implications: it is possible to significantly improve the performance of future home energy reports through targeted treatment.