RESEARCH BRIEF • JULY 2024

Dynamic Targeting: Experimental Evidence from Energy Rebate Programs

Based on BFI Working Paper No. 2024-72, "Dynamic Targeting: Experimental Evidence from Energy Rebate Programs," by Takanori Ida, Kyoto University; Takunori Ishihara, Kyoto University of Advanced Science; Koichiro Ito, University of Chicago; Daido Kido, Otaru University of Commerce; Toru Kitagawa, Brown University; Shosei Sakaguchi, The University of Tokyo; and Shusaku Sasaki, Osaka University

Targeting a policy's beneficiaries based on their responses to past policies leads to larger gains than targeting based solely on pre-intervention information.

A policy's effectiveness often hinges on whether it reaches the right people. Thanks to recent advances in big data and machine learning, researchers have revealed the gains from directing benefits like the Supplemental Nutrition Assistance Program (SNAP) and Social Security to the neediest recipients. While prior research on **policy targeting** has emphasized **static interventions**, where beneficiaries are evaluated and receive benefits once, many policies involve **dynamic interventions** over multiple periods. In this paper, the authors propose a new method to design and evaluate repeated interventions, which they apply to a **randomized controlled trial** (RCT) on an energy rebate program.

The authors recruited 2,400 Japanese households for their RCT, and offered participants assigned to the treatment a rebate to reduce their electricity consumption during peak hours. The RCT compares three different types of policy targeting approaches: static targeting, where pre-intervention information (like household demographics and historical electricity usage) is used to determine treatment assignments, dynamic targeting, where information gathered from the first period is used to inform treatment decisions in the second period, and non-targeting, where no information is used to differentiate among households.

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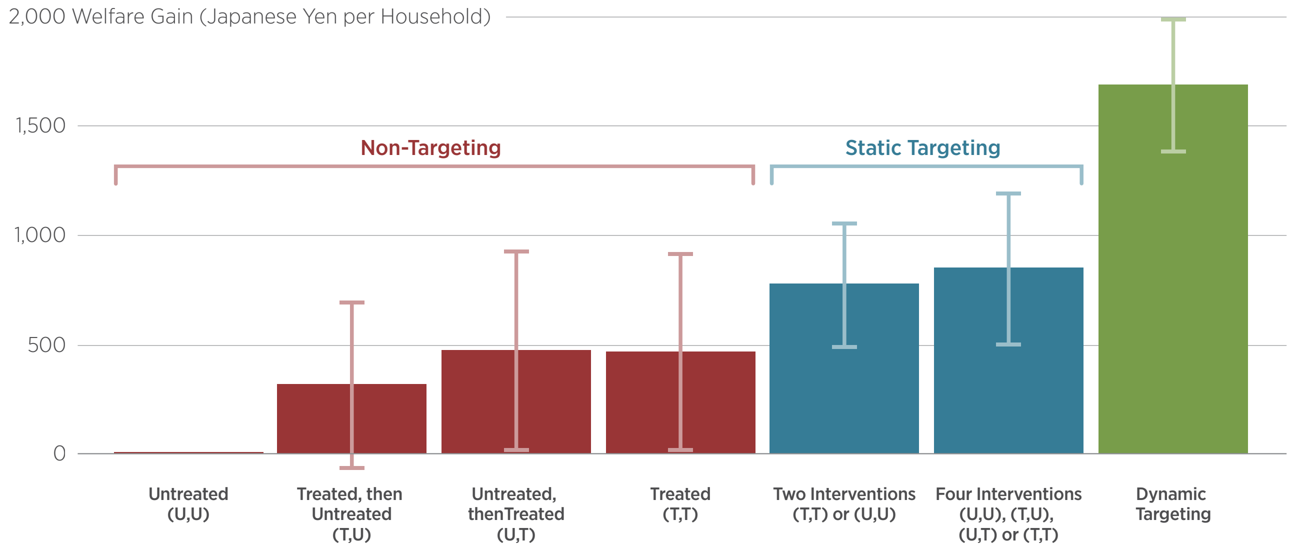
Policy Targeting: Directing specific interventions toward certain groups or areas to achieve optimal outcomes

Static Intervention: A treatment strategy where assignments remain fixed and do not adapt based on individual responses or new information.

Dynamic Intervention: A treatment strategy that adapts and optimizes assignments over time based on observed responses and updated information.

Randomized Controlled Trial (RCT): A study design where participants are randomly assigned to either a treatment group or a control group to objectively measure the effects of an intervention.

Figure 1 • Reporting on Stock Returns



Note: This pair of figures illustrates the relationship between stock market returns and the probability of reporting, compared to the continuous ranked probability score (CRPS). The top figure shows the frequency of reporting for different levels of stock market returns, and the bottom figure shows the relationship between stock market returns and the CRPS (measured in log points), highlighting how more extreme returns lead to higher CRPS scores. In both graphs, the vertical bars show the 95% confidence intervals.

Using each of these targeting approaches, the authors assign participants to four groups: one untreated in both periods, one treated in both periods, and two that alternate between being treated in the first period and untreated in the second, and vice versa. They summarize their groups as follows: (U,U), (T,T), (U,T), and (T,U), where U denotes *untreated* and T signifies *treated*. The authors compare energy conservation across their groups, and find the following:

- While static targeting significantly enhances welfare benefits compared to non-targeting policies, dynamic targeting significantly augments these benefits, nearly doubling the **welfare gain** from static targeting policies.
- The authors attribute these gains to three key mechanisms: *learning*, where individuals who receive an intervention for multiple periods may learn to respond effectively; *habit formation*, where individuals develop habits of conserving electricity when exposed to the rebate program; and *screening*, where information gathered from earlier interventions informs later treatment allocation. Each of these mechanisms tends to vary widely across individuals.

In an era when policies are carefully directed towards certain beneficiaries, this research demonstrates the capacity to further optimize targeting using a dynamic approach. Furthermore, the authors identify considerable variation in the learning, habit formation, and screening effects across households, and their research illustrates how to leverage these differences to devise optimal dynamic targeting strategies.

Welfare Gain: The increase in overall well-being or economic benefit resulting from a specific policy or intervention.

READ THE WORKING PAPER

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ABOUT OUR SCHOLAR

Koichiro Ito

Professor, Harris School of Public Policy

THE UNIVERSITY OF CHICAGO
HARRIS SCHOOL OF PUBLIC POLICY