Choosing Who Chooses?

Selection-Driven Targeting in Energy Rebate Programs

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Targeting is a central interest in policy design

- Many policies are costly. Causal effects can be heterogeneous
- How to maximize a policy's impact given a limited budget?
- Policymakers could target individuals who generate large welfare gains

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- Examples:
  - Job training program (Kitagawa and Tetenov, 2018)
  - Supplemental Nutrition Assistance Program (Finkelstein and Notowidigdo, 2019)
  - Disability program (Deshpande and Li, 2019)
  - Energy efficiency (Burlig, Knittel, Rapson, Reguant, and Wolfram, 2020)
  - Behavioral nudge (Knittel and Stolper, 2019)
  - Dynamic electricity pricing (Ito, Ida, and Tanaka, 2021)

Two competing perspectives on targeting

Who should choose treatment, **planner** or **each individual**?

1. **Planner**: paternalistic/centralized approach
   - Planners choose treatments based on individual's observable information (X)
   - Manski (2004): Use RCT data to identify CATE(X) and use them for targeting

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2. **Individual**: autonomous approach
   - Each individual selects own treatment. They may have important information unobservable to the planner
   - Policymakers could take advantage of this self-selection (e.g., Alatas, Purnamasari, Wai-Poi, Banerjee, Olken, and Hanna 2016, Ito, Ida, and Tanaka 2021)

Which approach is better?

- E.g., Job training program for unemployed workers:
  - Should planner assign based on their $X =$(education,earnings)?
  - Should planner let the unemployed select their preferred treatment?
- Can individuals perform rational choices? Planner's objective and individuals objectives aligned?

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"... one should be skeptical of broad assertions that individuals are better informed than planners and hence make better decisions. Of course, skepticism of such assertions does not imply that planning is more effective than laissez-faire. Their relative merits depend on the particulars of the choice problem."

from "Public Policy in an Uncertain World"
by Manski (2013)

This paper

- **Our Idea**: **let's exploit advantages of both approaches!**
- **Method**: Data from properly designed RCT & the Empirical Welfare Maximization (EWM) to identify
  - Individual type x who should be "Treated (T)"
  - Individual type x who should be "Untreated (U)"
  - Individual type x who should "Select (S)"

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- **Our Idea**: **let's exploit advantages of both approaches!**
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- **Contributions**:
  - Propose a sampling design for learning selection-driven targeting
  - Estimate an optimal selection-driven targeting policy
  - Implement the idea to energy saving rebate programs in Japan
  - Show that it improves social welfare compared to paternalism or autonomy only.

Outline

Framework

Setup

- Consider a net social welfare gain (W) from a costly treatment
- Define three potential outcomes (heterogeneous across individuals)
  - $W(T)$: a potential outcome if an individual is treated
  - $W(U)$: a potential outcome if an individual is untreated
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- Having observed x, which arm the planner should assign?
  - Assign S if $E[W(S)|x] \geq \max\{E[W(U)|x], E[W(T)|x]\}$, i.e., selection works in line with planner's goal
  - Assign T if $E[W(T)|x] \geq \max\{E[W(U)|x], E[W(S)|x]\}$ or Assign U if $E[W(U)|x] \geq \max\{E[W(T)|x], E[W(S)|x]\}$, i.e., selection does not yield a preferable treatment for the planner

Optimal targeting

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- Targeting policy $G := (G_T, G_U, G_S)$, a partition of the space of X.

- The average welfare contribution under a targeting policy G:

$$\mathcal{W}(G) \equiv E[\sum_{j \in \{T,U,S\}} W(j) \cdot 1\{X \in G_j\}].$$

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- Find an optimal policy G^* that maximizes $\mathcal{W}(G)$.
- **Data?**: RCT (or a quasi-experiment) with three treatment arms. $\{W_i, D_i, X_i\}$ for $i = 1, ..., n$, where $D_i \in \{T, U, S\}$ is randomly assigned (possibly cond. on X_i)

Empirical Welfare Maximization (EWM) method

- Using the RCT data, construct an empirical analogue of $\mathcal{W}(G)$ is

$$\widehat{\mathcal{W}}(G) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j \in \{T,U,S\}} \left(\frac{W_i \cdot 1\{D_i = j\}}{P(D_i = j \mid X_i)} \cdot 1\{X_i \in G_j\} \right).$$

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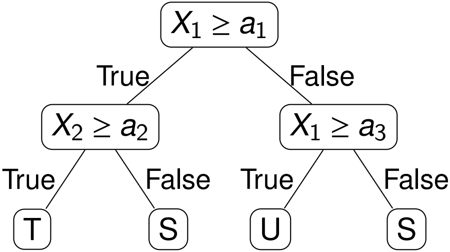
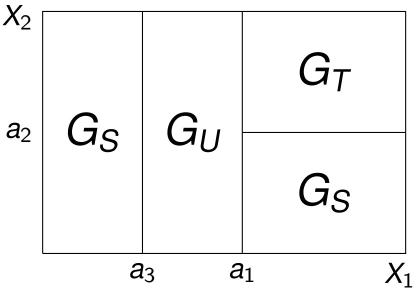
- We use a class of policy trees (Zhou, Athey, Wager, 2018) with depth 6.

Policy tree

Depth 2 policy tree



Partition of $\mathcal{X}$ by a depth 2 policy tree



Field Experiment

Field experiment

1. Treatment: A peak-hour rebate program for residential electricity use
   - Partner: Japanese Ministry of the Environment
   - Peak-hour: 1 pm to 5 pm in critical peak days in summer 2020
   - Baseline: Average hourly usage in the same hours before experiment
   - Customers were unaware of baseline until experiment began
   - All customers were on "non-dynamic retail prices"
   - Rebate = $\$1/\text{kWh}$ conservation $\approx$ peak-hour wholesale price
   - Implementation cost per consumer = 291.1 JPY ($\approx$ cents)
   - Welfare gain = a reduction in (long-run) DWL – implementation cost
2. Experimental sample: 3,870 households in Japan
   - Not a random sample of population
   - Recruitment by mail and email
3. Randomization:
   - Control: 1,577, Treatment: 1,486, Selection: 807
   - Opt-in rate is 37.17%

Balance check

	Sample mean by group [standard deviation]			Difference in sample means (standard error)		
	Untreated	Treated	Selection	U vs. T	U vs. S	T vs. S
Peak hour usage (Wh)	192	190	189	2.57	2.87	0.29
	[141]	[138]	[134]	(5.04)	(6.00)	(5.97)
Pre-peak hour usage (Wh)	179	176	180	3.79	-1.11	-4.89
	[137]	[135]	[142]	(4.93)	(6.00)	(6.03)
Post-peak hour usage (Wh)	299	297	293	1.94	6.02	4.08
	[175]	[171]	[174]	(6.26)	(7.55)	(7.53)
Number of people at home	2.48	2.44	2.47	0.04	0.01	-0.03
	[1.24]	[1.24]	[1.27]	(0.05)	(0.05)	(0.06)
Self efficacy in energy conservation	3.45	3.46	3.49	-0.01	-0.04	-0.02
(1-5 Likert scale)	[0.85]	[0.85]	[0.83]	(0.03)	(0.04)	(0.04)
Household income (JPY10,000)	645	613	637	31.69	8.46	-23.23
	[399]	[362]	[391]	(13.80)	(17.17)	(16.29)

- Electricity usage variables are based on usage in the pre-experimental period.

Impacts on ln(peak-hour usage): ITT analysis

		Peak hour usage – Pre-peak hour usage (in pre-experiment)		Peak hour usage – Post-peak hour usage (in pre-experiment)	
	All	Low	High	Low	High
100% T	-0.097	-0.108	-0.079	-0.089	-0.094
	(0.021)	(0.028)	(0.031)	(0.030)	(0.028)
100% S	-0.052	-0.022	-0.073	-0.070	-0.023
	(0.027)	(0.034)	(0.041)	(0.037)	(0.037)
Number of customers	3,870	1,935	1,935	1,937	1,933
Number of obs.	1,176,480	588,240	588,240	589,152	587,328
p-value (T = S)	0.088	0.013	0.880	0.595	0.047
Take-up rate	37.2%	36.9%	37.4%	39.9%	34.7%

- We obtain substatial heterogeneity by consumer covariates including peak – pre-peak hour usage, the number of people at home, self-efficacy in energy conservation, etc.
- Standard errors are clustered at the customer level

Optimal Policy Design

Result 1: Targeting and welfare gains

Policy	Share of customers in each arm			Welfare Gains
	Untreated	Treated	Selection	
100% untreated	100.0%	0.0%	0.0%	0.0 (——)
100% treated	0.0%	100.0%	0.0%	120.7 (98.8)
100% self-selection	0.0%	0.0%	100.0%	180.6 (112.1)
Selection-absent targeting	47.6%	52.4%	0.0%	387.8 (55.7)
Selection-driven targeting	23.9%	31.4%	44.7%	553.7 (68.0)

- Note: the net welfare gain is in JPY ($\approx$ cents) per week per consumer

Result 1: Targeting and welfare gains

	Difference in Welfare Gains
Selection-absent targeting vs. 100% T	267.2 (99.7)
Selection-absent targeting vs. 100% S	207.3 (116.9)
Selection-driven targeting vs. 100% T	433.0 (106.8)
Selection-driven targeting vs. 100% S	373.1 (113.3)
Selection-driven vs. Selection-absent targeting	165.8 (61.1)

1. Selection-absent targeting (*T* or *U*) improves welfare compared to 100% U or 100% T
2. **Selection-driven targeting (*T* or *U* or *S*) dominates any of 100% assignments and selection-absent targeting**

What delivers welfare gain?

- Suppose that the exclusion restriction for ”who chooses” holds

$$W(S) = W(T) \cdot 1\{Z(S) = T\} + W(U) \cdot 1\{Z(S) = U\}$$

- LATEs for *compliers* and *non-compliers* in each assigned policy group $j \in \{T, U, S\}$ can be identifed

$$\begin{aligned} \text{LATE(complier)} &:= E[W(T) - W(U) \mid Z(S) = T, X \in G_j] \\ \text{LATE(non-complier)} &:= E[W(T) - W(U) \mid Z(S) = U, X \in G_j] \end{aligned}$$

  where $\{Z(S) = T\}$ are those who would choose T if they were assigned to S-arm

- Investigate these LATEs when G is the estimated Selection-Driven Targeting (SDT) policy

Result 2: Mechanism of welfare gain

	Recommended arm j by SDT		
	U	T	S
Take-up rate $P(Z(S) = T \mid X \in G_j^{\mathrm{SDT}})$	39.5% (3.7%)	41.7% (3.0%)	37.5% (2.5%)
LATE for compliers $E[W(T) - W(U) \mid Z(S) = T, X \in G_j^{\mathrm{SDT}}]$	−2334.6 (475.6)	162.8 (362.3)	2061.7 (348.2)
LATE for non-compliers $E[W(T) - W(U) \mid Z(S) = U, X \in G_j^{\mathrm{SDT}}]$	29.1 (305.5)	1019.4 (239.6)	−823.0 (184.5)

- Column U (individuals who we find should be assigned to U)
  - If they are asked to select, 40% would take treatment
  - However, those taking up treatment lower the social welfare, i.e., selection would lower social welfare
  - The planner should choose the treatment U for them

Result 2: Mechanism of welfare gain

	Recommended arm j by SDT		
	U	T	S
Take-up rate i.e., $P(Z(S)=T \mid X \in G_j^{\text{SDT}})$	39.5% (3.7%)	41.7% (3.0%)	37.5% (2.5%)
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- Column T (individuals who we find should be assigned to T)
  - If they are asked to select, 58% would not take up the treatment
  - However, those not taking up treatment can increase the social welfare, i.e., selection would forgo the welfare gain
  - The planner should choose the treatment T for them

Result 2: Mechanism of welfare gain

	Recommended arm j by SDT		
	U	T	S
Take-up rate i.e., $P(Z(S) = T \mid X \in G_j^{\text{SDT}})$	39.5% (3.7%)	41.7% (3.0%)	37.5% (2.5%)
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- Column S (individuals who we find should be assigned to S)
  - If they are asked to select, 38% would take treatment
  - LATE(compliers) is positive & LATE(Non-compliers) is negative, i.e., selection improves social welfare
  - The planner should let them choose their preferred treatment

What about equity/redistributions?

- One public concern of the rebate program is equity/redistribution. E.g., rich households tend to own many electric appliances and has a larger margin for saving energy compared with poor households.
- EWM approach can easily incorporate the planner's redistributive preference.
- Weighted-average social welfare function (Saez, 2003)

$$\mathcal{W}^{v}(G) = \frac{1}{n}\sum_{i=1}^{n}\omega^{v}(\text{income}_i)\left[\sum_{j\in\{T,U,S\}}\left(\frac{W_i \cdot 1\{D_i = j\}}{P(D_i = j \mid X_i)} \cdot 1\{X_i \in G_j\}\right)\right].$$

where $\omega^{v}(\text{income}_i) \propto \left(\frac{1}{\text{income}_i}\right)^{v}$.

Result 3: Efficiency-equity trade-offs

	Efficiency gain	Average rebate by the quartiles of household income			
		[0%,25%]	(25%,50%]	(50%,75%]	(75%,100%]
Utilitarian ($v = 0$)	553.7 (68.0)	72.8 (10.3)	93.7 (12.9)	144.1 (19.1)	148.9 (18.9)
Weighted SW ($v = 1$)	431.2 (69.2)	77.0 (13.0)	132.3 (17.4)	140.2 (18.1)	116.5 (17.6)
Weighted SW ($v = 2$)	366.1 (69.3)	105.2 (14.8)	115.7 (16.5)	109.9 (16.2)	119.2 (20.8)

- This suggests there is efficiency-equity trade-offs

Concluding remarks

1. We propose a sampling design, estimation methods, and welfare assessment, of an optimal targeting policy that exploits the advantages of paternalism and autonomy
2. We implement to idea on the energy rebate programs in Japan and show significant welfare gains can be obtained by mixing paternalistic and autonomous assignments.
3. In causal inference, observational data with selection is not considered to be useful. From the policy design perspective, data with selection, combined with experimental data, can be useful for designing a better policy.