INGENIERIA INDUSTRIAL
UNIVERSIDAD DE CHILE

IN4402: Aplicaciones de Probabilidades y Estadística

CAUSAL RANDOM FOREST - APPLICATION

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ELECTRICITY CONSERVATION

THEORY AND PRACTICE

- Energy conservation is essential for environment protection
- What works better on changing people's behaviour?
  - Higher pricing in peak hours?
  - Rebate?
  - Non-monetary? (feedback)

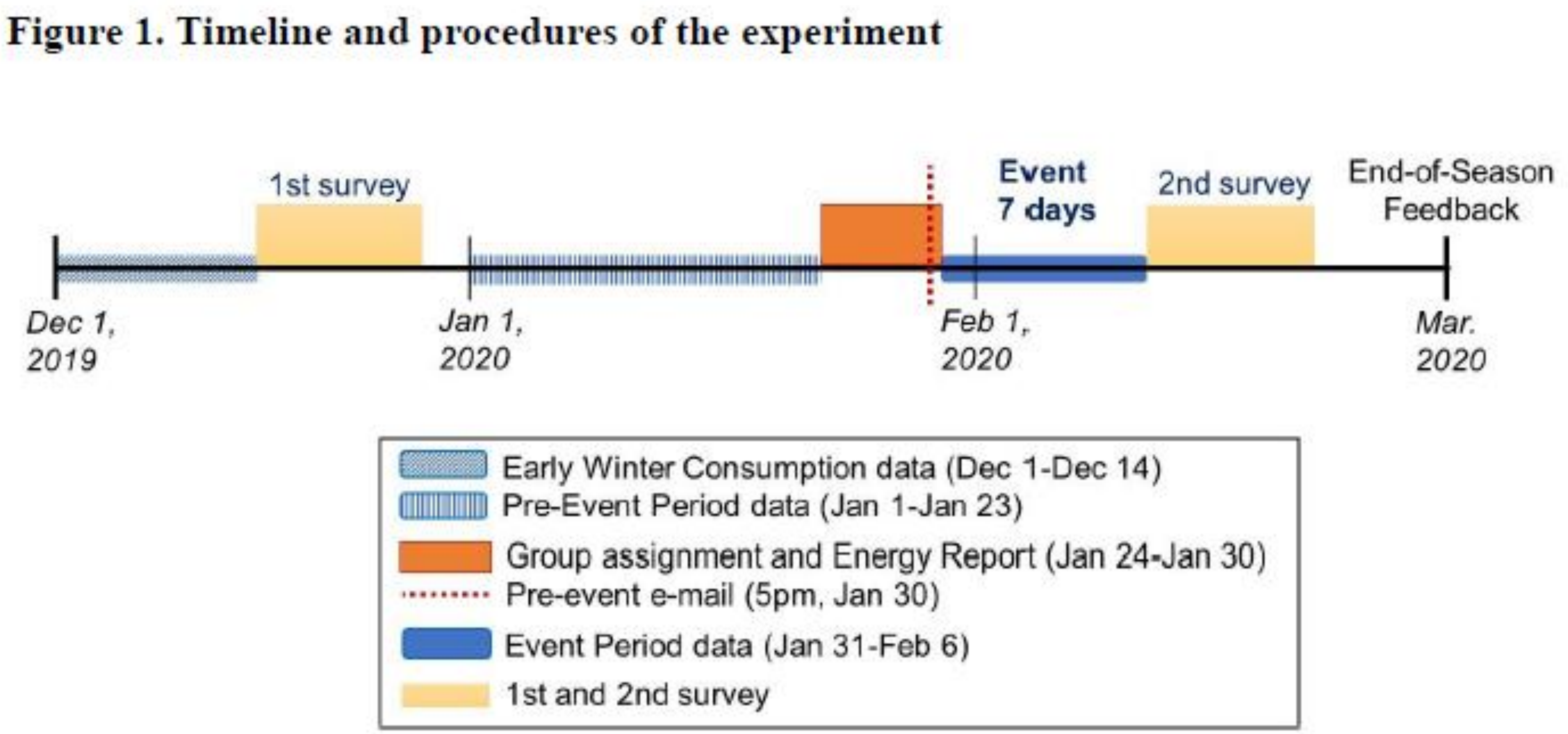
Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020). *Heterogeneous Treatment Effects of Nudge and Rebate: Causal Machine Learning in a Field Experiment on Electricity Conservation* (No. e-20-003).

EXPERIMENTAL DESIGN
FIELD EXPERIMENT

- From November 2019 to February 2020 field experiment in Japan
- Sample of 954 households
- Random assignment:

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020). *Heterogeneous Treatment Effects of Nudge and Rebate: Causal Machine Learning in a Field Experiment on Electricity Conservation* (No. e-20-003).

EXPERIMENTAL DESIGN
FIELD EXPERIMENT DESIGN



Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020). *Heterogeneous Treatment Effects of Nudge and Rebate: Causal Machine Learning in a Field Experiment on Electricity Conservation* (No. e-20-003).

EXPERIMENTAL DESIGN
BALANCE CHECK

	Control (N=327)	Rebate (N=313)		Nudge (N=314)	
	Average	Difference	p-value	Difference	p-value
Early Winter (December 1–14)					
Electricity use (kWh /day)	13.818	0.084	0.909	−0.114	0.877
Electricity use (kWh /peak-time)	2.761	0.010	0.941	0.006	0.967
Pre-Event Period (January 1–23)					
Electricity use (kWh /day)	16.876	0.091	0.920	0.009	0.992
Electricity use (kWh /peak-time)	3.343	−0.009	0.957	0.051	0.770
Rebate Baseline (January 17–23)					
Electricity use (kWh /day)	17.029	0.082	0.929	0.018	0.984
Electricity use (kWh /peak-time)	3.383	−0.054	0.750	0.072	0.688
Demographic Characteristics					
Household size (persons)	2.700	0.012	0.898	−0.028	0.772
Number of A/Cs	2.994	0.143	0.294	0.025	0.855
Home size (Square meter)	116.667	−2.242	0.551	−0.297	0.938
Household income (JPY/million)	6.343	−0.366	0.232	−0.070	0.828
All electric house (Dummy)	0.440	−0.054	0.168	−0.039	0.317

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020). *Heterogeneous Treatment Effects of Nudge and Rebate: Causal Machine Learning in a Field Experiment on Electricity Conservation* (No. e-20-003).

RESULTS

ATE ESTIMATION BY DIFFERENCE IN DIFFERENCE

Table 2. ATEs of rebate and nudge

	All household		Subgroup			
	N=954		Less (N=581)		More (N=355)	
Rebate	−0.043	***	−0.056	***	−0.025	
	(0.013)		(0.016)		(0.023)	
Nudge	−0.007		−0.038	**	0.036	
	(0.013)		(0.015)		(0.024)	
Observations	214,173		126,598		83,372	

Predicted by RF

Note: **p<0.05, ***p<0.01. This table shows the DID estimation results for Equation (2). Standard errors are reported in parentheses. We used the natural logarithm of electricity usage for the dependent variable; hence, the treatment effects may be approximately interpreted in percentage terms.

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020). *Heterogeneous Treatment Effects of Nudge and Rebate: Causal Machine Learning in a Field Experiment on Electricity Conservation* (No. e-20-003).

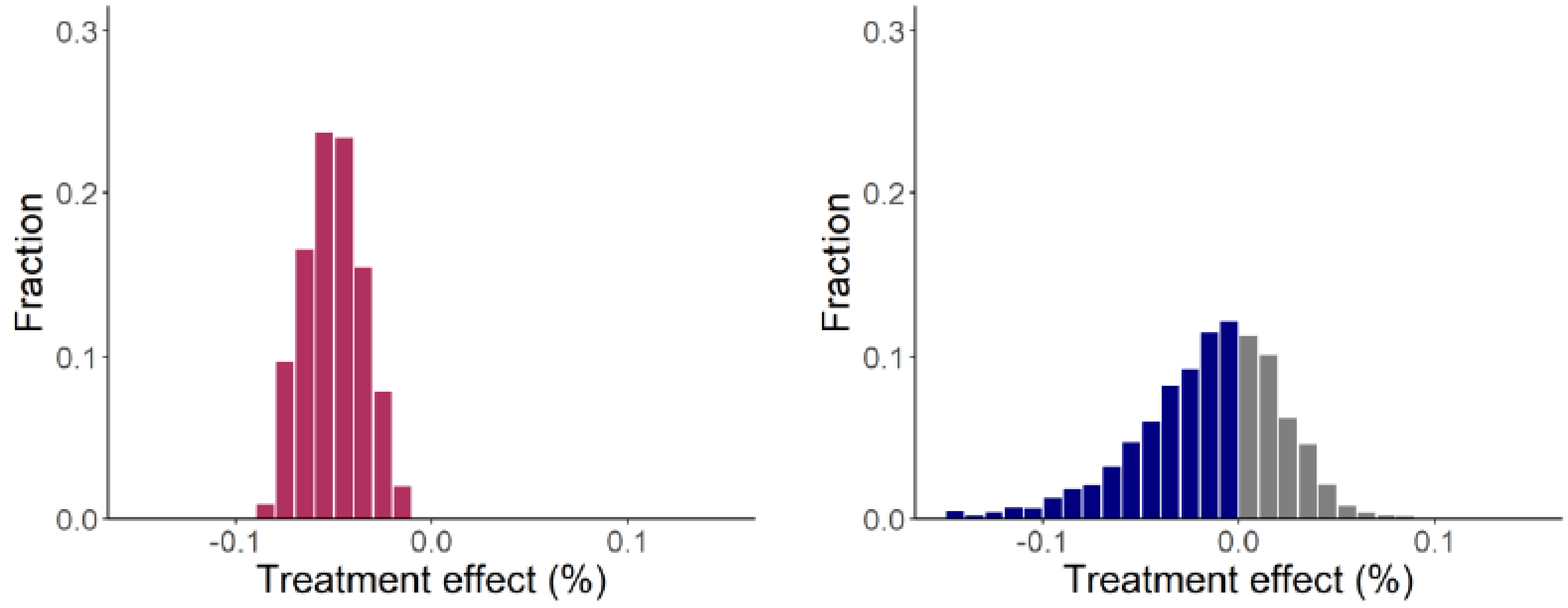
- Generalized Random Forests algorithm:

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020). *Heterogeneous Treatment Effects of Nudge and Rebate: Causal Machine Learning in a Field Experiment on Electricity Conservation* (No. e-20-003).

HETEROGENEITY IN TREATMENT EFFECTS
GENERALIZED RANDOM FORESTS

- Results:

Figure 4. Distributions of heterogenous treatment effects



(A) Rebate (B) Nudge

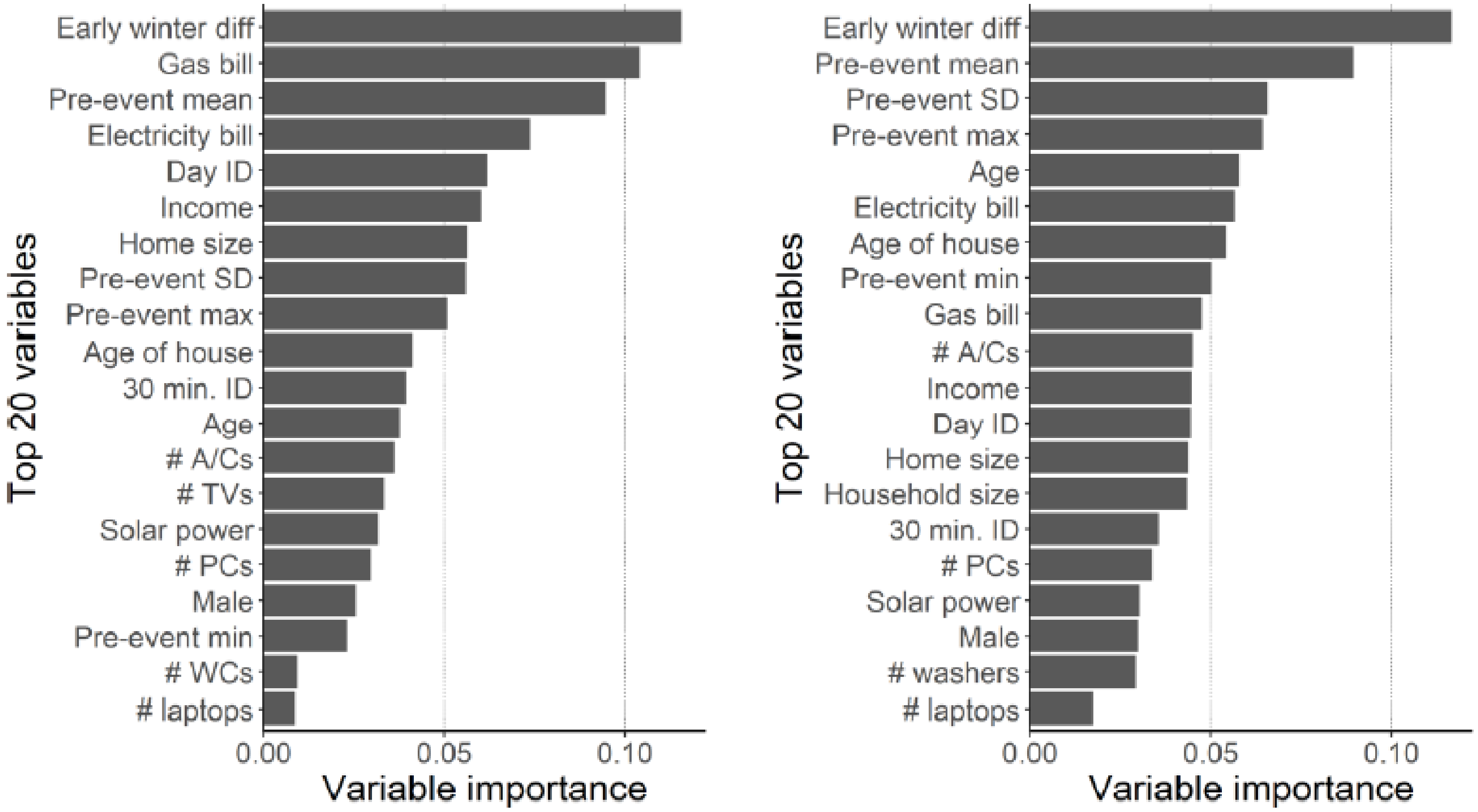
	Rebate		Nudge
Average treatment effects	−0.052	***	−0.014
	(0.016)		(0.015)

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020)

HETEROGENEITY IN TREATMENT EFFECTS
GENERALIZED RANDOM FORESTS

Figure 5. Key variables for growing trees

- Key Variables:



(A) Rebate (B) Nudge

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020)

HETEROGENEITY IN TREATMENT EFFECTS
GENERALIZED RANDOM FORESTS

- Testing heterogeneity in out of sample observations:

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020)

HETEROGENEITY IN TREATMENT EFFECTS
GENERALIZED RANDOM FORESTS

- Testing heterogeneity in out of sample observations:

Table 4. Results of the slope test

	ATE (γ)	Heterogeneity (η)
Rebate	−0.044	1.641
	[−0.073, −0.015]	[0.050, 3.296]
Nudge	−0.008	1.410
	[−0.032, 0.016]	[0.051, 2.793]

Note: The numbers in brackets represent the 90% confidence interval proposed by Chernozhukov et al. (2019). The number of iterations is 1000.

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020)

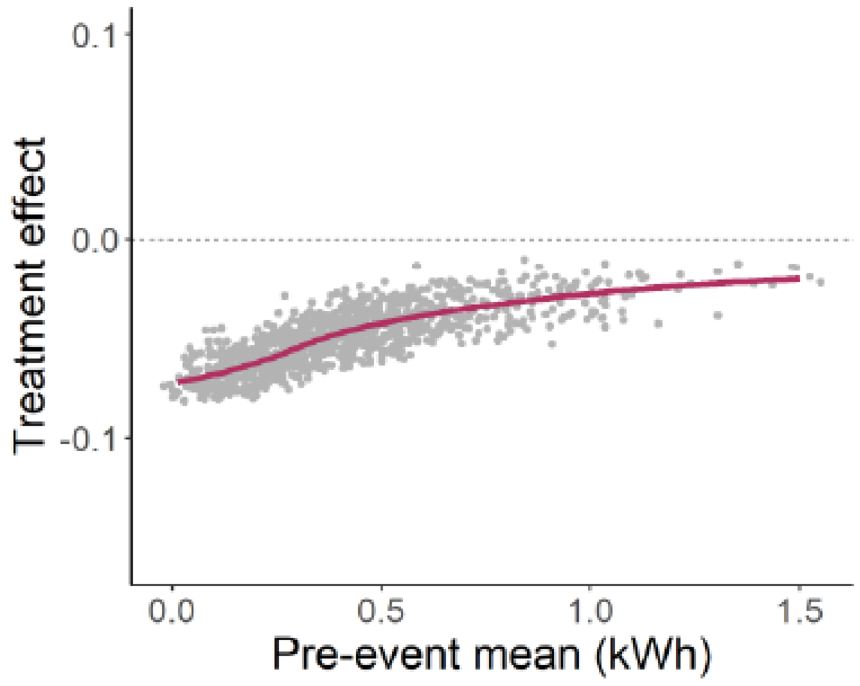
POLICY OPTIMIZATION
BEING MORE EFFECTIVE WITH TREATMENT

- Some formalities:
  - Value of a policy
  - Improvement of a policy

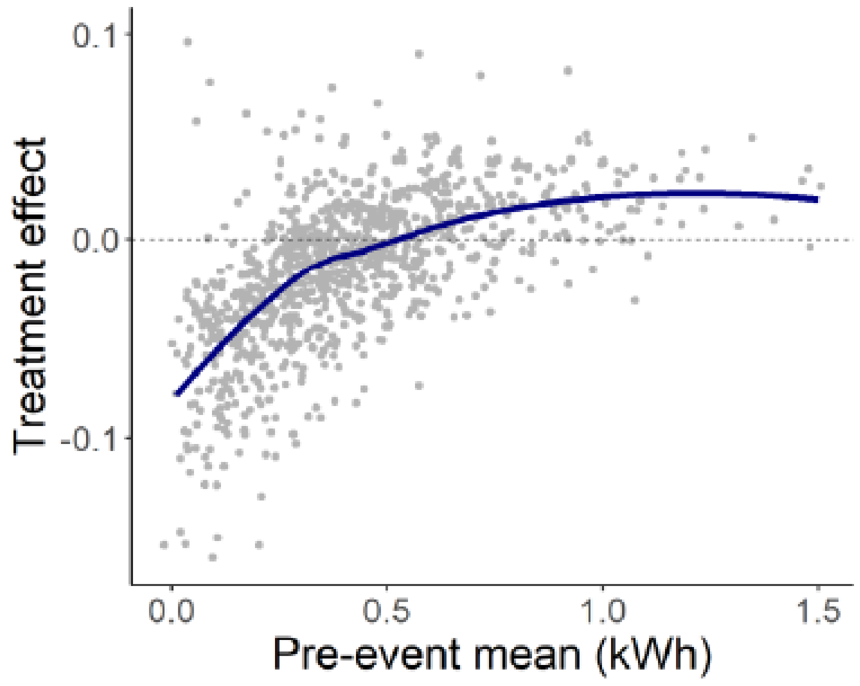
Source: Estimation of Heterogeneous Treatment Effects prepared for “Machine Learning and Causal Inference” class
Susan Athey, Stefan Wager, Vitor Hadad, Sylvia Klosin, Nicolaj Muhelbach, Xinkun Nie, Matt Schaelling
May 07, 2020 -> https://gsbdbi.github.io/ml_tutorial/hte_tutorial/hte_tutorial.html

POLICY OPTIMIZATION
BEING MORE EFFECTIVE WITH TREATMENT

Figure 6. Mean electricity usage in the pre-event period and treatment effects



(A) Rebate



(B) Nudge

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020)

Table 5. Improvement in treatment effects by targeting

	Net treatment effects	
	Uniform	Targeting
Rebate	−5.02%	−5.02%
	(1.49)	(1.49)
Nudge	−1.25%	−3.29%
	(5.77)	(3.60)
Optimum targeting	−5.61%	
	(2.33)	

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020)

POLICY OPTIMIZATION
BEING MORE EFFECTIVE WITH TREATMENT

- Designing optimal policy as a function of observables

SUMMARY

CAUSAL RANDOM FOREST APLICATION

- Energy conservation is important but it is hard to achieve
- The authors compare Monetary vs. Non.monetary type of treatment
  - Monetary treatment shows positive effect on all sample
  - Non-monetary treatment shows effect on those previously “concious”
- Treatment could be optimized if both treatments are mixed between people:
  - Less costs of expensive treatment (rebate)
  - More effects on less costly treatment (nudge)

Source: Murakami, K., Shimada, H., Ushifusa, Y., & Ida, T. (2020)