Peaking Interest: How awareness drives the effectiveness of time-of-use electricity pricing

Brian C. Prest[1]

Camp Resources XXIV

August ~~7~~ **8**, 2017

[1]Ph.D. Candidate, UPEP, Duke University, brian.prest@duke.edu

Overview

- **Goal**
  - Using machine learning to estimate heterogeneous treatment effects from TOU electricity pricing & info. provision
  - **Meaning?** "Under what conditions do consumers change their electricity consumption in response to prices that vary by time of day?"

Overview

- **Goal**
  - Using machine learning to estimate heterogeneous treatment effects from TOU electricity pricing & info. provision
  - **Meaning?** "Under what conditions do consumers change their electricity consumption in response to prices that vary by time of day?"
- **Heterogeneity**
  - **Why?** targeting, understanding mechanisms
  - **Context**: rich dataset from experiment on Irish households
  - **Problem**: multiple testing
  - **What's needed**: parsimonious way to estimate heterogeneity in many dimensions in a robust manner → machine learning

Results

- **Average TOU pricing effect**: -9% peak consumption

Results

- **Average TOU pricing effect**: -9% peak consumption
- **Robust Sources of Heterogeneity**:

Results

- **Average TOU pricing effect**: -9% peak consumption
- **Robust Sources of Heterogeneity**:
    - ***Key result***: Unaware households don't respond (-2%, insignif.)

Results

- **Average TOU pricing effect**: -9% peak consumption
- **Robust Sources of Heterogeneity**:
  - ***Key result***: Unaware households don't respond (-2%, insignif.)
  - Low energy consuming households don't respond

Results

- **Average TOU pricing effect**: -9% peak consumption
- **Robust Sources of Heterogeneity**:
    - ***Key result***: Unaware households don't respond (-2%, insignif.)
    - Low energy consuming households don't respond
    - Info. provision amplifies effects up to 2x (even conditional on awareness)

Results

- **Average TOU pricing effect**: -9% peak consumption
- **Robust Sources of Heterogeneity**:
  - ***Key result***: Unaware households don't respond (-2%, insignif.)
  - Low energy consuming households don't respond
  - Info. provision amplifies effects up to 2x (even conditional on awareness)
  - Size of price change doesn't matter

Results

- **Average TOU pricing effect**: -9% peak consumption
- **Robust Sources of Heterogeneity**:
  - ***Key result***: Unaware households don't respond (-2%, insignif.)
  - Low energy consuming households don't respond
  - Info. provision amplifies effects up to 2x (even conditional on awareness)
  - Size of price change doesn't matter
  - Nothing else matters (out of 150+ household characteristics)

Results

- **Average TOU pricing effect**: -9% peak consumption
- **Robust Sources of Heterogeneity**:
  - ***Key result***: Unaware households don't respond (-2%, insignif.)
  - Low energy consuming households don't respond
  - Info. provision amplifies effects up to 2x (even conditional on awareness)
  - Size of price change doesn't matter
  - Nothing else matters (out of 150+ household characteristics)
- **Other findings**:

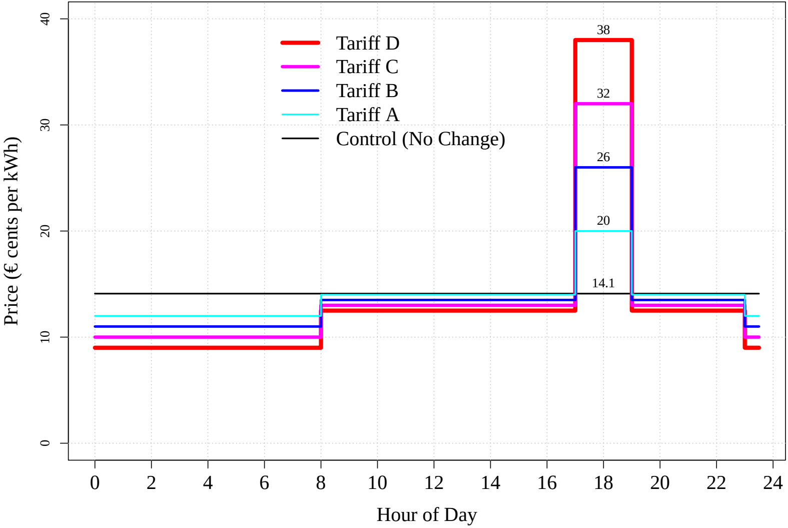
Results

- **Average TOU pricing effect**: -9% peak consumption
- **Robust Sources of Heterogeneity**:
  - ***Key result***: Unaware households don't respond (-2%, insignif.)
  - Low energy consuming households don't respond
  - Info. provision amplifies effects up to 2x (even conditional on awareness)
  - Size of price change doesn't matter
  - Nothing else matters (out of 150+ household characteristics)
- **Other findings**:
  - Can't reliably predict who will be aware

Results

- **Average TOU pricing effect**: -9% peak consumption
- **Robust Sources of Heterogeneity**:
    - ***Key result***: Unaware households don't respond (-2%, insignif.)
    - Low energy consuming households don't respond
    - Info. provision amplifies effects up to 2x (even conditional on awareness)
    - Size of price change doesn't matter
    - Nothing else matters (out of 150+ household characteristics)
- **Other findings**:
    - Can't reliably predict who will be aware
    - Real-time pricing not necessarily more efficient than TOU

What is Time-of-Use Pricing?



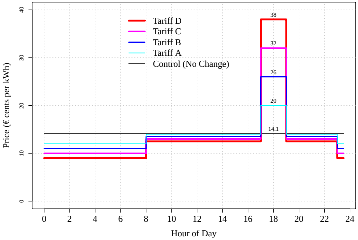
Experimental Details

- 2009: Households recruited; baseline data collected; pre-trial survey; randomized to treatment/control
- 2010: Treatment period
- 2011: Follow-up survey

	Bi-Monthly Bill / Energy Statement	Monthly Bill / Statement	In-Home Display	Load Reduction Incentive	Control
Tariff A	195	216	205	216	0
Tariff B	80	87	72	81	0
Tariff C	222	217	202	213	0
Tariff D	80	87	78	77	0
Control	0	0	0	0	678

Experimental Details

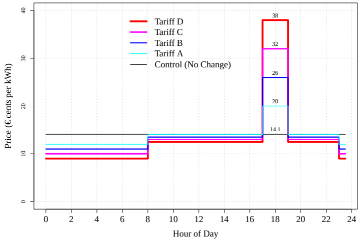
- 2009: Households recruited; baseline data collected; pre-trial survey; randomized to treatment/control
- 2010: Treatment period
- 2011: Follow-up survey



	Bi-Monthly Bill / Energy Statement	Monthly Bill / Statement	In-Home Display	Load Reduction Incentive	Control
Tariff A	195	216	205	216	0
Tariff B	80	87	72	81	0
Tariff C	222	217	202	213	0
Tariff D	80	87	78	77	0
Control	0	0	0	0	678

Experimental Details

- 2009: Households recruited; baseline data collected; pre-trial survey; randomized to treatment/control
- 2010: Treatment period
- 2011: Follow-up survey



	Bi-Monthly Bill / Energy Statement	Monthly Bill / Statement	In-Home Display	Load Reduction Incentive	Control
Tariff A	195	216	205	216	0
Tariff B	80	87	72	81	0
Tariff C	222	217	202	213	0
Tariff D	80	87	78	77	0
Control	0	0	0	0	678

Data

- **Household Electricity Consumption** ($N \times T \approx 77$ million)
  - $N \approx 3,000$ households
  - $T \approx 26,000$ half-hours each

Data

- **Household Electricity Consumption** ($N \times T \approx 77$ million)
  - $N \approx 3,000$ households
  - $T \approx 26,000$ half-hours each
- **Survey data**: > 150 complete variables on...
  - ***Family characteristics***: Employment status, education, social class, household size, #adults, #children, etc.
  - ***House characteristics***: age, #rooms, #bedrooms, style, insulation, window glazing, etc.
  - ***Appliance & electronics characteristics***: home heating fuel types, water heating fuel types, #immersion heaters, #dishwashers, #washing machines, #tumble dryers, #TVs (by size), #computers, #game consoles, internet access, etc.
  - ***Attitudinal/Behavioral***: Attitudes towards energy, environment, etc., expected achievable energy savings, appliance & electronics usage behavior, reasons for participating in the program, etc.
  - ***Post-experiment survey***: questions about experience with program

Results

Results

1. Average Treatment Effect

Results

1. Average Treatment Effect
2. Heterogeneity

Results

1. Average Treatment Effect
2. Heterogeneity
3. Policy Targeting

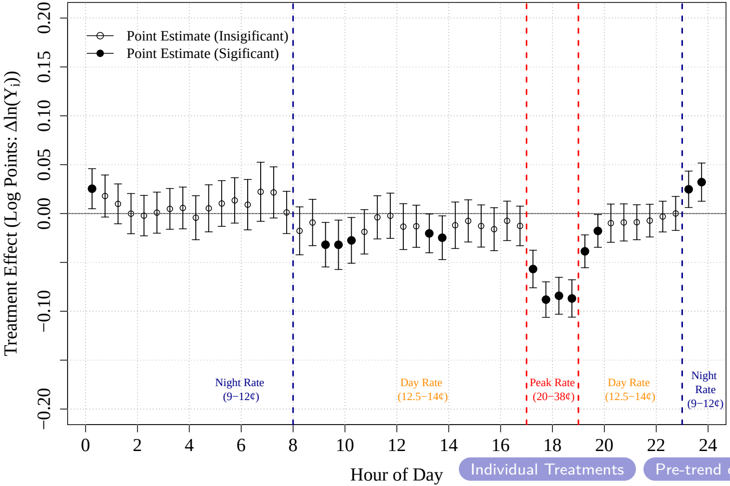
Average Treatment Effect

Difference-in-Differences (All Treatments)

$$\ln(kwh_{i,h,t}) = \beta_h Treatment_{i,h,t} + \alpha_{i,h} + \lambda_{m,h} + \epsilon_{i,h,t}$$

Difference-in-Differences (All Treatments)

$$\ln(kwh_{i,h,t}) = \beta_h Treatment_{i,h,t} + \alpha_{i,h} + \lambda_{m,h} + \epsilon_{i,h,t}$$



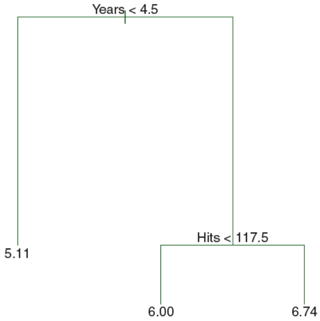
Individual Treatments | Pre-trend check

Heterogeneity

Methods: Athey-Imbens & Extensions

Athey & Imbens (2016)

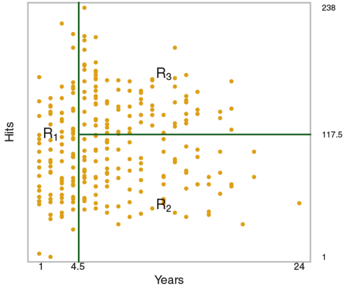
- Estimates CATEs w/ trees ("Conditional" ATE)



Extensions in this paper

- Diff-in-diff (vs. "diff")
  - Replace Y_i with ΔY_i
- Multiple treatment groups
  - Allow splitting on treatment

Details



How does Athey-Imbens work? (Simple Version)

Y_i ... outcome, W_i ... treatment, p ... share treated $(\frac{n_T}{n})$

$$Y_i^* \equiv Y_i \frac{W_i - p}{p(1-p)} = \begin{cases} Y_i/p & \text{if } W_i = 1 \\ -Y_i/(1-p) & \text{if } W_i = 0 \end{cases}$$

How does Athey-Imbens work? (Simple Version)

Y_i ... outcome, W_i ... treatment, p ... share treated $(\frac{n_T}{n})$

$$Y_i^* \equiv Y_i \frac{W_i - p}{p(1-p)} = \begin{cases} Y_i/p & \text{if } W_i = 1 \\ -Y_i/(1-p) & \text{if } W_i = 0 \end{cases}$$

$$\begin{aligned} \frac{1}{n}\sum_i Y_i^* &= \frac{1}{n}\left[\sum_{i\in\mathcal{S}_T}\frac{Y_i}{p} + \sum_{i\in\mathcal{S}_C}\frac{-Y_i}{1-p}\right] = \frac{1}{n}\left[\sum_{i\in\mathcal{S}_T}\frac{Y_i}{n_T/n} + \sum_{i\in\mathcal{S}_C}\frac{-Y_i}{n_C/n}\right] \\ &= \frac{1}{n_T}\sum_{i\in\mathcal{S}_T} Y_i - \frac{1}{n_C}\sum_{i\in\mathcal{S}_C} Y_i \\ &= LATE \end{aligned}$$

How does Athey-Imbens work? (Simple Version)

Y_i ... outcome, W_i ... treatment, p ... share treated $(\frac{n_T}{n})$

$$Y_i^* \equiv Y_i \frac{W_i - p}{p(1-p)} = \begin{cases} Y_i/p & \text{if } W_i = 1 \\ -Y_i/(1-p) & \text{if } W_i = 0 \end{cases}$$

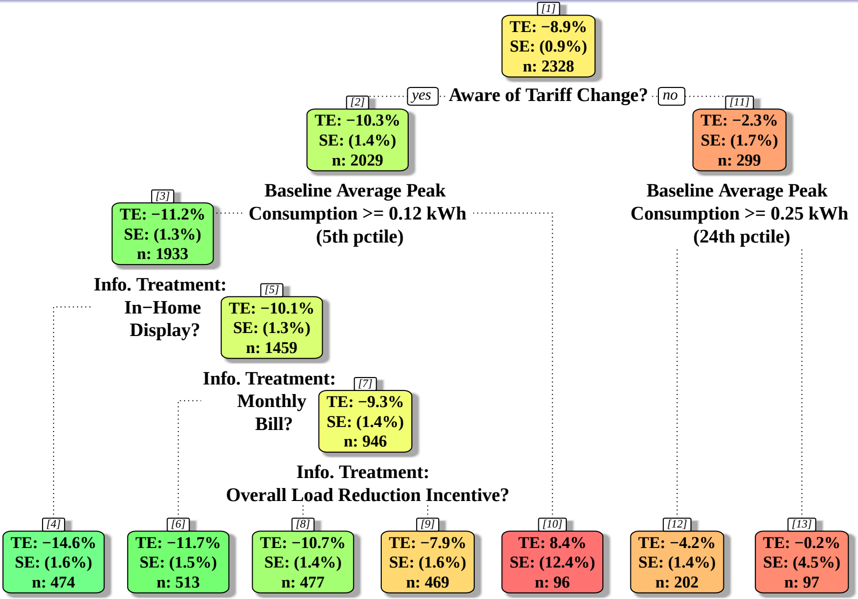
$$\begin{aligned} \frac{1}{n}\sum_i Y_i^* &= \frac{1}{n}\left[\sum_{i\in\mathcal{S}_T} \frac{Y_i}{p} + \sum_{i\in\mathcal{S}_C} \frac{-Y_i}{1-p}\right] = \frac{1}{n}\left[\sum_{i\in\mathcal{S}_T} \frac{Y_i}{n_T/n} + \sum_{i\in\mathcal{S}_C} \frac{-Y_i}{n_C/n}\right] \\ &= \frac{1}{n_T}\sum_{i\in\mathcal{S}_T} Y_i - \frac{1}{n_C}\sum_{i\in\mathcal{S}_C} Y_i \\ &= LATE \end{aligned}$$

Intuitively, model Y_i^* as a flexible function of X_i:

$$E[Y_i^*|X_i] = f(X_i) = \text{“}ATE(X_i)\text{”}$$

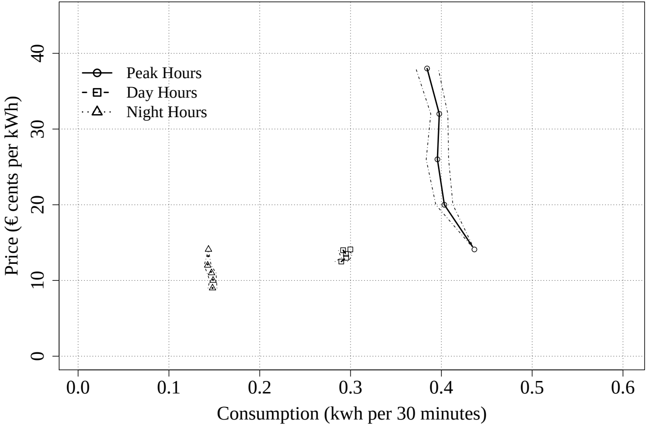
Heterogeneity Results

Heterogeneity Results



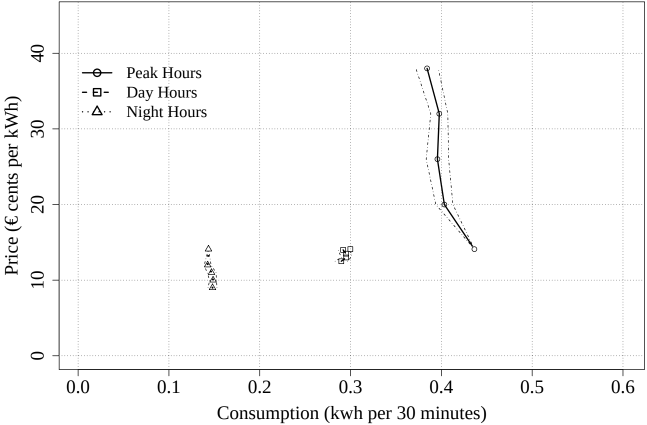
Robustness Checks: Propensity Tree | “Honest” Tree

Aside: Mean Demand Curves, by Period of Day



Heterogeneous Demand

Aside: Mean Demand Curves, by Period of Day



- Commonly-used constant elasticity assumption is *invalid*
- Real-time pricing not necessarily better (& possibly worse)

Heterogeneous Demand

Policy Targeting

Targeting Likely-Aware Households

- Target on awareness?
  - Why? Costs, customer blowback
- Classification problem: $P(Aware_i = 1|X_i) = f(X_i)$
  - Same problem: many variables, multiple testing
  - Solution: Post-selection Lasso for variable selection/elimination

Lasso Post-Selection LPMs on Awareness

	Aware of Tariff Change (Indicator)		
	LPM	Lasso-Min	Lasso-1SE
Internet Access in Home (Indicator)	0.06	0.06	0.13
Use Internet Regularly (Indicator)	0.02	0.01	
Water Heating Fuel: Oil (Indicator; "none" omitted)	0.05	0.04	
Number of Dishwashers in Home	0.03	0.04	
Number of Desktop Computers in Home	0.02	0.01	
Expect Participating in Trial Will Reduce My Bill (Indicator)	0.05	0.06	
Female Respondent (Indicator)	0.04	0.04	
Social Class: AB (Highest) (Indicator)	-0.02	0.02	
Education: Third (e.g., University) (Indicator)	0.05	0.04	
Info. Treatment: In-Home Display (Indicator; Bi-monthly Bill omitted)	0.05	0.05	
Info. Treatment: Monthly bill (Indicator; Bi-monthly Bill omitted)	0.04	0.05	
Info. Treatment: OLR (Indicator; Bi-monthly Bill omitted)	-0.01		
R^2	0.12	0.07	0.03
Adjusted R^2	0.07	0.07	0.03
Observations	2,328	2,328	2,328
Number of Covariates	123	17	1
Number of Covariates Not Shown	111	6	0
Number of Covariates Significant (5% level)	14 (11.4%)	na	na

Conclusion

1. Awareness of the TOU pricing is key to effectiveness
   $\Rightarrow$ Awareness not predictable, so focus on information

Conclusion

1. Awareness of the TOU pricing is key to effectiveness
   - $\Rightarrow$ Awareness not predictable, so focus on information
2. Small consumers don't respond (in levels or percentages)
   - $\Rightarrow$ Target larger consumers

Conclusion

1. Awareness of the TOU pricing is key to effectiveness
   - $\Rightarrow$ Awareness not predictable, so focus on information
2. Small consumers don't respond (in levels or percentages)
   - $\Rightarrow$ Target larger consumers
3. Information provision amplifies effects up to 2x, even among aware households
   - $\Rightarrow$ Information is important

Conclusion

1. Awareness of the TOU pricing is key to effectiveness
   - ⇒ Awareness not predictable, so focus on information
2. Small consumers don't respond (in levels or percentages)
   - ⇒ Target larger consumers
3. Information provision amplifies effects up to 2x, even among aware households
   - ⇒ Information is important
4. Size of price change doesn't matter

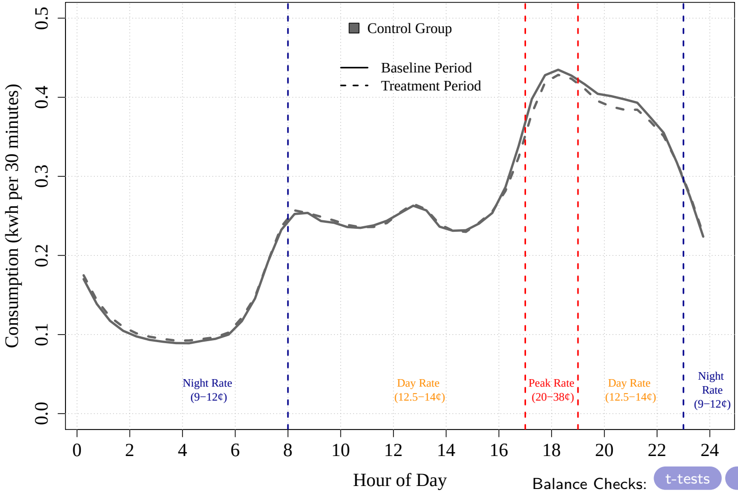
Conclusion

1. Awareness of the TOU pricing is key to effectiveness
   - $\Rightarrow$ Awareness not predictable, so focus on information
2. Small consumers don't respond (in levels or percentages)
   - $\Rightarrow$ Target larger consumers
3. Information provision amplifies effects up to 2x, even among aware households
   - $\Rightarrow$ Information is important
4. Size of price change doesn't matter

Getting prices exactly right isn't as important as getting people to pay attention in the first place

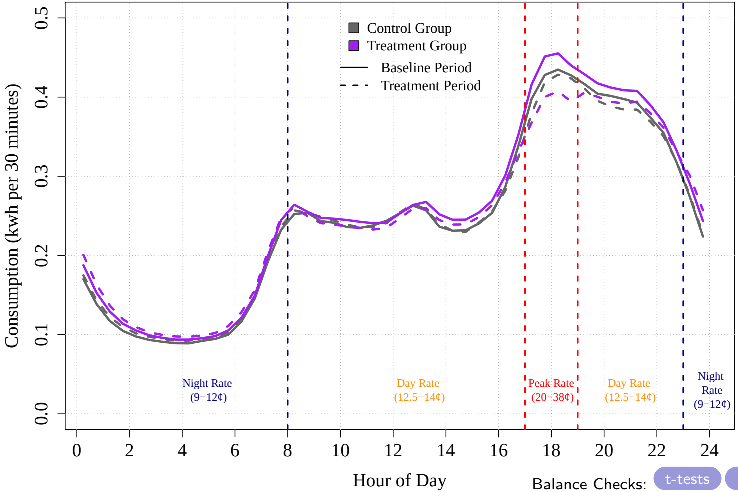
Thanks!

Average Consumption Profiles, by Group & Period



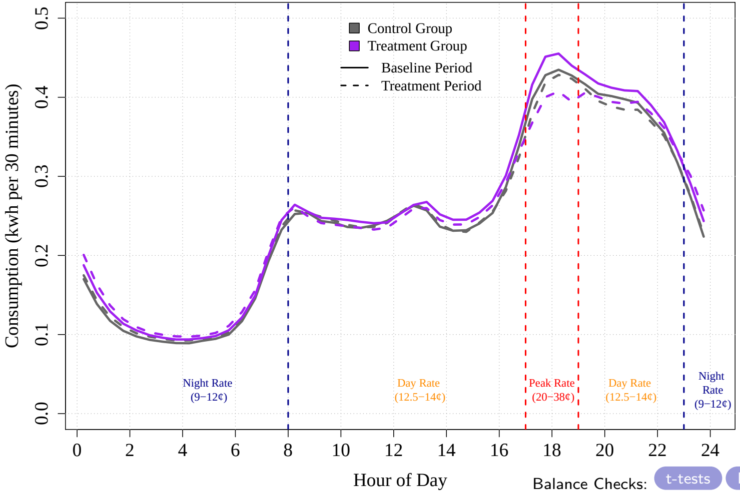
Balance Checks: t-tests LPM

Average Consumption Profiles, by Group & Period



Balance Checks: t-tests LPM

Average Consumption Profiles, by Group & Period



Balance Checks: t-tests LPM

Treatment/control are unbalanced ⇒ need diff-in-diff

Balance Checks: t-tests

	Variable	Control Mean	Treatment Mean	t-statistic	p-value
	Unbalanced Variables ($\alpha < 0.05$)				
1	Employment status: Retired (Indicator)	0.38	0.31	3.40	0.001
2	Number of Large Televisions (21+ inch)	1.19	1.31	-3.36	0.001
3	Number of Electronics	3.74	4.04	-3.03	0.003
4	Age Group: 65+ (Indicator)	0.28	0.23	2.79	0.01
5	Has Children Under 15 in Home (Indicator)	0.23	0.28	-2.78	0.01
6	Number of Residents	2.60	2.76	-2.65	0.01
7	Social Class: AB (Highest) (Indicator)	0.12	0.15	-2.58	0.01
8	Education: Primary only (Indicator)	0.15	0.11	2.51	0.01
9	Baseline Average Consumption (Night Hours)	0.14	0.15	-2.42	0.02
10	Internet Access in Home (Indicator)	0.66	0.71	-2.24	0.02
11	Number of Desktop Computers	0.48	0.53	-2.18	0.03
12	Number of Children Under 15 in Home	0.43	0.52	-2.11	0.04
13	Housing Status: Own with Mortgage (Indicator)	0.35	0.40	-2.09	0.04
14	Others in Household Use Internet Regularly (Indicator)	0.53	0.57	-2.01	0.04
	Selected Balanced Variables ($\alpha \geq 0.05$)				
15	Baseline Average Consumption (Peak Hours)	0.42	0.44	-1.85	0.07
16	Number of Adults in Home	2.16	2.24	-1.74	0.08
17	Cook stove type: Electric (Indicator)	0.72	0.69	1.62	0.10
18	Number of Laptop Computers	0.65	0.71	-1.61	0.11
19	Baseline Average Consumption (Day Hours)	0.29	0.30	-1.56	0.12
20	Unemployed, not seeking job (Indicator)	0.03	0.04	-1.52	0.13
21	Home Heat: Solid Fuel (Indicator)	0.29	0.26	1.46	0.14
22	Interested in changing energy use for environment*	1.38	1.34	1.41	0.16
23	Female (Indicator)	0.47	0.50	-1.02	0.31
24	Education: Secondary to Certificate (Indicator)	0.16	0.17	-0.86	0.39
25	Satisfied with billing frequency*	2.84	2.86	-0.47	0.64
	Observations	3,006			
	Number of Variables Tested	122			
	Number of Variables Not Shown	97			
	Number of Variables Significant (5% level)	14			
	Share of of Variables Significant (5% level)	11.5%			

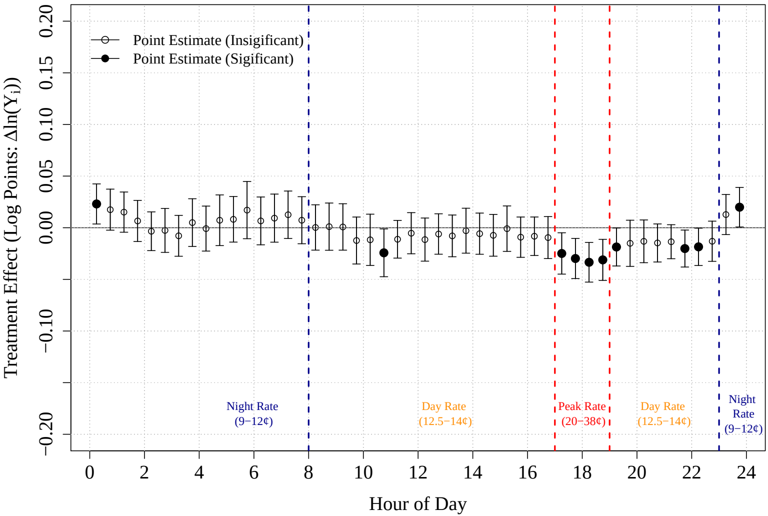
Return to main

Balance Checks: LPM

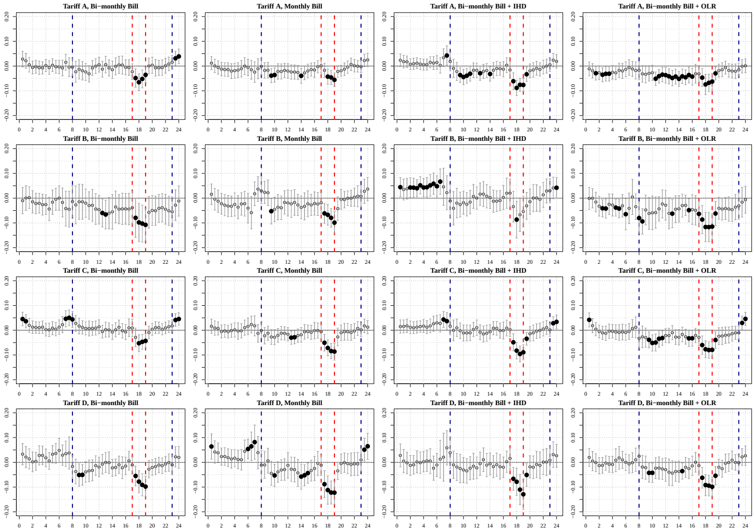
	Dependent variable:
	Treated (Indicator)
Baseline Average Consumption (Peak Hours)	0.03
	(0.07)
Baseline Average Consumption (Night Hours)	0.14
	(0.15)
Baseline Average Consumption (Day Hours)	-0.09
	(0.12)
Number of Large Televisions (21+ inch)	0.02**
	(0.01)
Age Group: 65+ (Indicator)	0.13
	(0.11)
Number of Adults in Home	0.01
	(0.01)
Internet Access in Home (Indicator)	0.01
	(0.02)
Number of Desktop Computers in Home	0.01
	(0.02)
Others in Household Use Internet Regularly (Indicator)	-0.003
	(0.02)
Cook stove type: Electric (Indicator)	-0.13**
	(0.06)
Observations	3,006
R^2	0.03
Adjusted R^2	-0.01
Number of Covariates	109
Number of Covariates Not Shown	100
Number of Covariates Significant (5% level)	2
Share of Covariates Significant (5% level)	1.8%

Return to main

Placebo test for TOU pricing: Weekends & Holidays

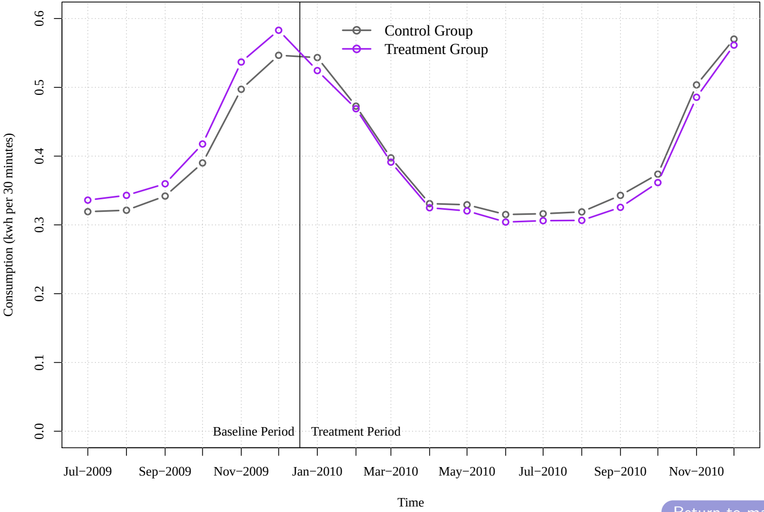


Diff-in-Diff (Individual Treatments)



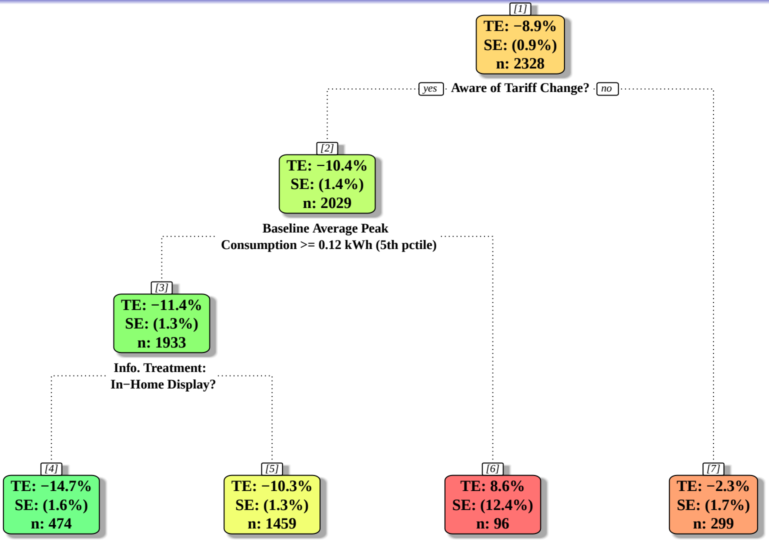
Return to main

Checking for pre-trends in peak consumption



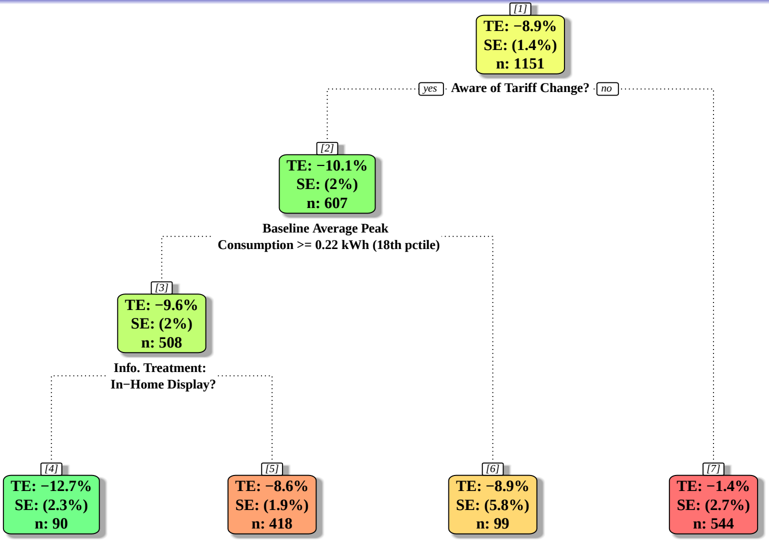
Return to main

Robustness Check: Propensity Tree



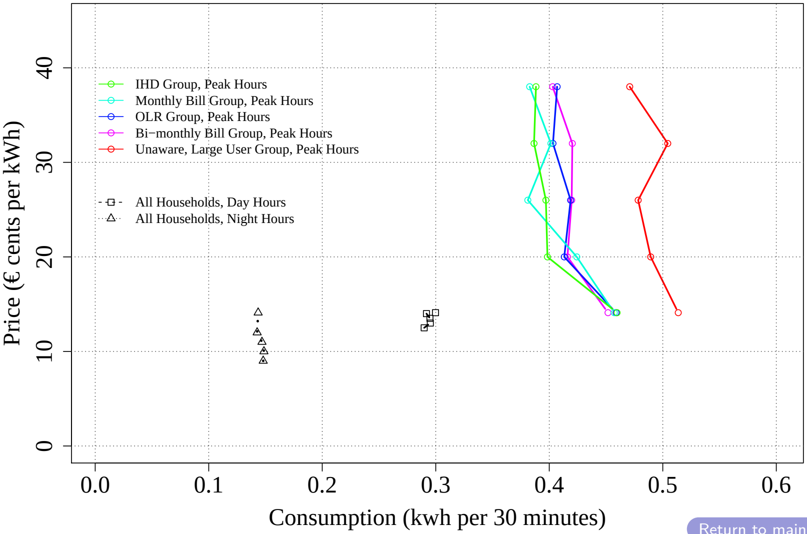
Return to main

Robustness Check: “Honest” Tree



Return to main

Heterogeneous Demand Curves



Return to main

Extension - Multiple Treatment Groups

For each control observation i and treatment $m \in \{1, ..., M\}$, generate a new pseudo-observation i_m with

$$\begin{aligned}
Y_{i_m} &\equiv Y_i \\
X_{i_m} &\equiv X_i \\
W_{i_m} &\equiv W_i \ (= 0) \\
\text{For } m' \in \{1, ..., M\} \quad W_{i_m}^{m'} &\equiv \begin{cases} 1 & \text{for } m' = m \\ 0 & \text{for } m' \neq m, \end{cases}
\end{aligned}$$

for a total of $M \times n_C$ control observations, replacing the n_C original ones

Extension - Multiple Treatment Groups

Transformed LATE:

$$\begin{aligned}
\frac{1}{n_T}\sum_{i\in\mathcal{S}_T} Y_i - \frac{1}{M\times n_C}\sum_{i\in\tilde{\mathcal{S}}_C} Y_i &= \frac{1}{n_T}\sum_{i\in\mathcal{S}_T} Y_i - \frac{1}{M\times n_C} M \sum_{i\in\mathcal{S}_C} Y_i \\
&= \frac{1}{n_T}\sum_{i\in\mathcal{S}_T} Y_i - \frac{1}{n_C}\sum_{i\in\mathcal{S}_C} Y_i \\
&= \hat{\tau},
\end{aligned}$$

which is the same as the LATE estimate of the untransformed data.

Return