FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Data-Driven Incentive Design for Residential Demand Response

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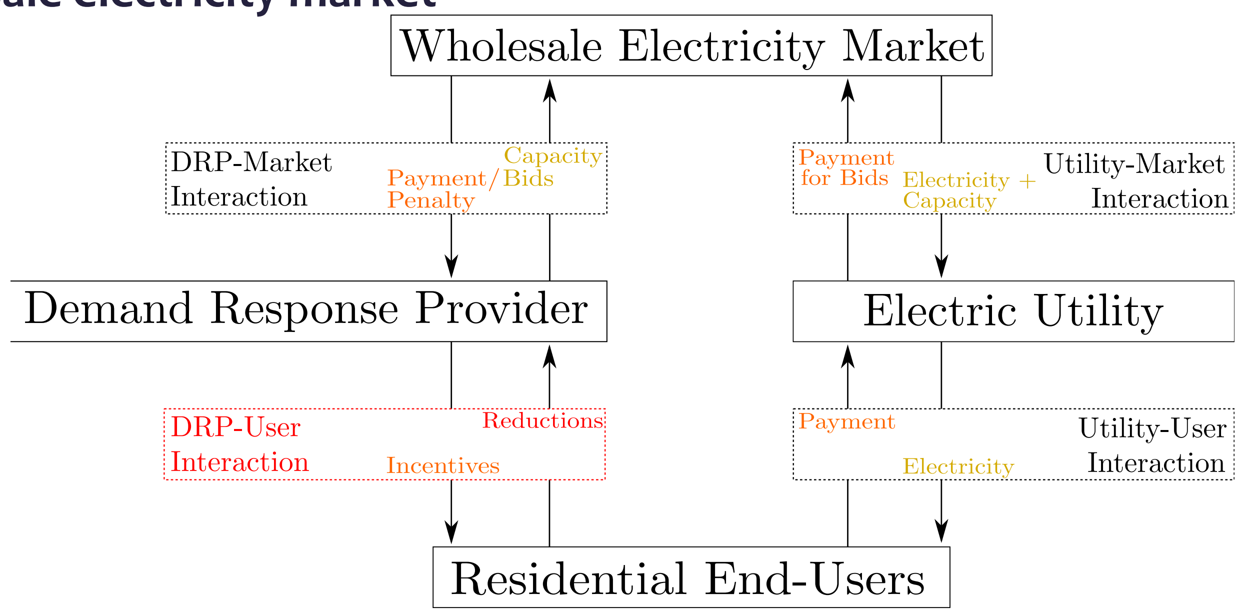
Residential Demand Response

- July 2015: California Public Utility Commission (CPUC) launches Demand Response Auction Mechanism (DRAM)
  - Electric utilities PG&E, SDG&E, and SCE required to implement pay-as-bid auction for Demand Response (DR) capacity
  - Demand Response Providers can **bid Proxy Demand Resources directly into the wholesale electricity market**



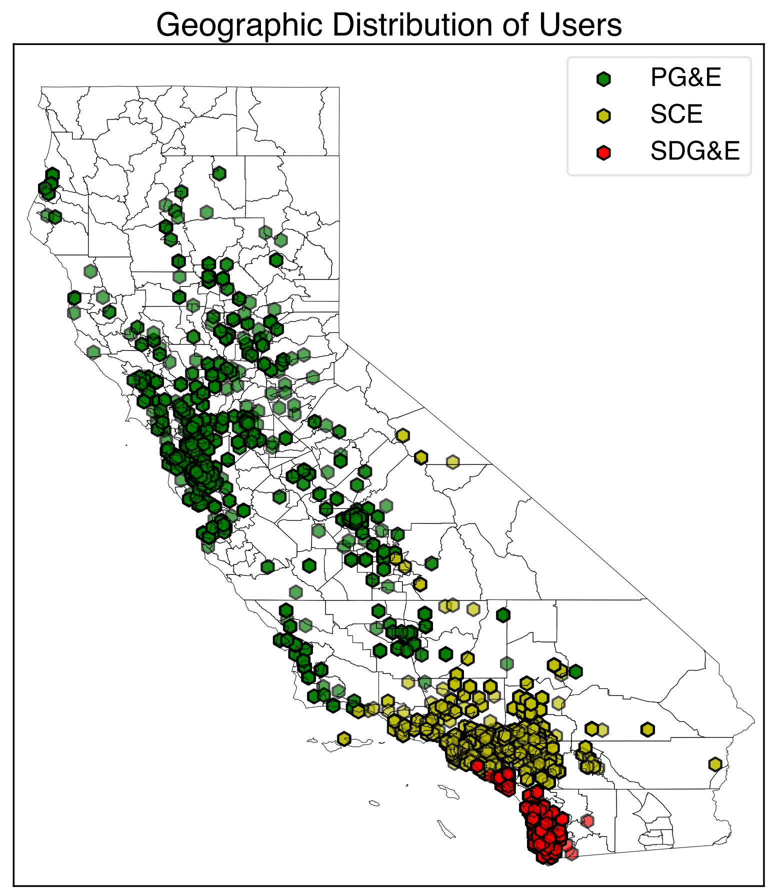
DRP – User Interaction

- DRP seeks to elicit reductions in consumption by end-users of electricity through properly designed monetary incentives

- Questions to answer:
  - How do users respond to monetary incentives for reduction?
  - How can this reduction be measured?
  - How heterogeneous are users in their responses?
  - Are there levers other than monetary incentives to elicit reductions (social comparison, peer effects, …)?

Treatment Effect Estimation

- Goal: Estimate the effect of a DR intervention program in California, USA
- Smart Meter Data of ~5,000 users
- Serviced by PG&E, SCE, SDG&E
- Hourly Demand Response Events
- ZIP codes for each user known

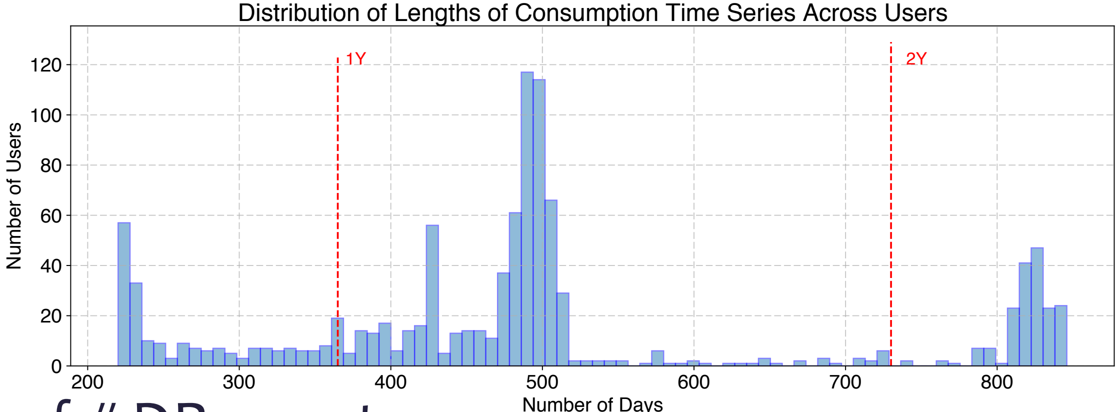


Data and Data Preparation

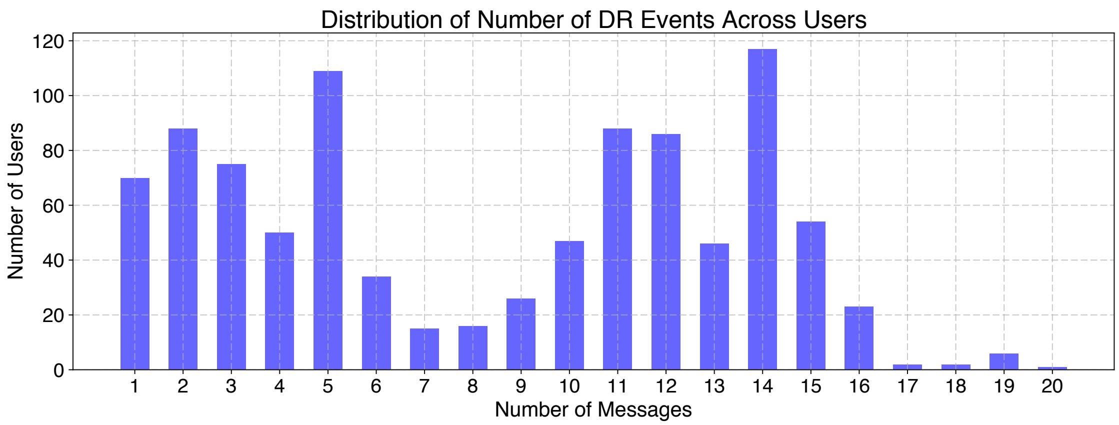
* Remove users with
  * … less than 7 months of time series data for consumption
  * … negative consumption values (due to net energy metering)
  * … corrupt smart meter readings
* 5,000 users --> 1,025 users
* Scrape ambient air temperatures at weather stations provided by California Irrigation Management Information System (CIMIS, publicly available)
* Linearly interpolate user-specific temperatures with Vincenty's formulae (distances on a sphere), using latitude+longitude

Summary Statistics for 1,025 “Clean” Users

* Distribution of lengths of available consumption time series:



* Distribution of # DR events across users:



Estimating the Counterfactual

* Potential Outcomes Framework [Rubin, 1974]:
* Each user $i \in \mathcal{I}$ is endowed with consumption time series $\mathbf{y}_i = \{y_{i1}, \ldots, y_{i\mathcal{T}}\}$ and covariates $X_i = \{\mathbf{x}_{i1}, \ldots, \mathbf{x}_{i\mathcal{T}}\}$
* Treatment and Control times:

$$\mathcal{C}_i = \{t \in \mathbb{T} \mid D_{it} = 0\}$$
$$\mathcal{T}_i = \{t \in \mathbb{T} \mid D_{it} = 1\}$$

* $D_{it} \in \{0, 1\}$ is treatment indicator
* Treatment and control data:

$$\mathcal{D}_{i,t} = \{(\mathbf{x}_{it}, y_{it}) \mid t \in \mathcal{T}_i\}$$
$$\mathcal{D}_{i,c} = \{(\mathbf{x}_{it}, y_{it}) \mid t \in \mathcal{C}_i\}$$

Estimating the Counterfactual (cont'd.)

* One-sample estimate of treatment effect:

$$\beta_{it}(\mathbf{x}_{it}) = y_{it}^1(\mathbf{x}_{it}) - y_{it}^0(\mathbf{x}_{it}) \quad \forall\, i \in \mathcal{I},\ t \in \mathbb{T}$$

* User-specific Individual Treatment Effect (ITE):

$$\beta_i := \mathbb{E}_{\mathcal{X}_i}\mathbb{E}_{t\in\mathcal{T}}[(y_{it}^1 - y_{it}^0) \mid \mathbf{x}_{it}] = \frac{1}{|\mathcal{T}_i|}\sum_{j\in\mathcal{T}_i}(y_{ij}^1 - y_{ij}^0)$$

* Unconfoundedness of Treatment Assignment Mechanism:

$$(y_{it}^0, y_{it}^1) \perp D_{it} \mid \mathbf{x}_{it} \quad \forall i \in \mathcal{I}, t \in \mathbb{T}$$

* Average Treatment Effect on the Treated (ATT):

$$\mathrm{ATT} = \mathbb{E}_{i\in\mathcal{I}}[\beta_i] = \frac{1}{|\mathcal{I}|}\sum_{i\in\mathcal{I}}\frac{1}{|\mathcal{T}_i|}\sum_{t\in\mathcal{T}_i}(y_{it}^1 - y_{it}^0)$$

Estimating the Counterfactual (cont'd.)

* Fundamental Problem of Causal Inference [Holland, 1986]:

$$y_{it} = y_{it}^0 + D_{it}(y_{it}^1 - y_{it}^0) \quad \forall\, t,\ \forall\, i \in \mathcal{I}$$

* Estimate counterfactuals with outcome model:

$$y_{it} = f_i(\mathbf{x}_{it}) + D_{it} \cdot \beta_{it}(\mathbf{x}_{it}) + \varepsilon_{it}$$

* Fit conditional mean function on control data $\mathcal{D}_{i,c}$
* Estimate counterfactual by evaluating $\hat{f}_i(\mathbf{x}_{it}), \quad t \in \mathcal{T}_i$
* Regression models used:
  * Ordinary Least Squares Regression (+L1, L2 penalized)
  * K-Nearest Neighbors Regression
  * Decision Tree Regression + Random Forest Regression

Nonparametric Estimation

* Naive differences in means between treatment outcomes and estimated counterfactuals is highly sensitive to outliers
* Robust estimation of treatment effect with Hodges-Lehmann Estimator:

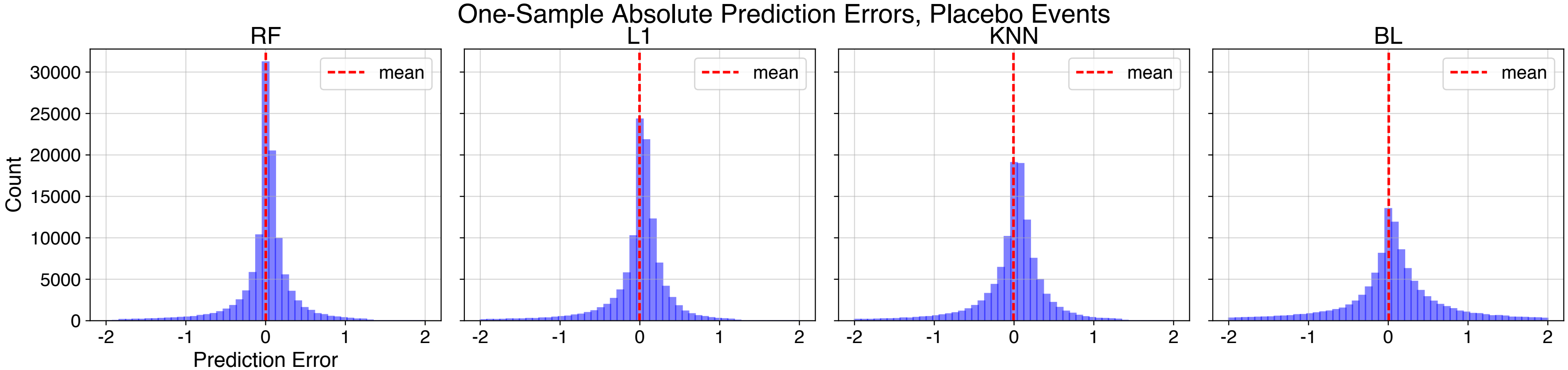
$$z_{it} = y^1_{it} - \hat{y}^0_{it}, \; t \in \mathcal{T}_i$$
$$\mathcal{Z}_i := \{(z_{i\mathcal{T}[t]} + z_{i\mathcal{T}[u]})/2 \mid 1 \leq t \leq u \leq |\mathcal{T}_i|\}$$
$$\hat{\beta}_i = \mathrm{median}(\mathcal{Z}_i)$$

* Hodges-Lehmann Estimate is associated with Wilcoxon Signed Rank Test. Can construct coverage probabilities for confidence intervals of $\hat{\beta}_i$ and p-values for

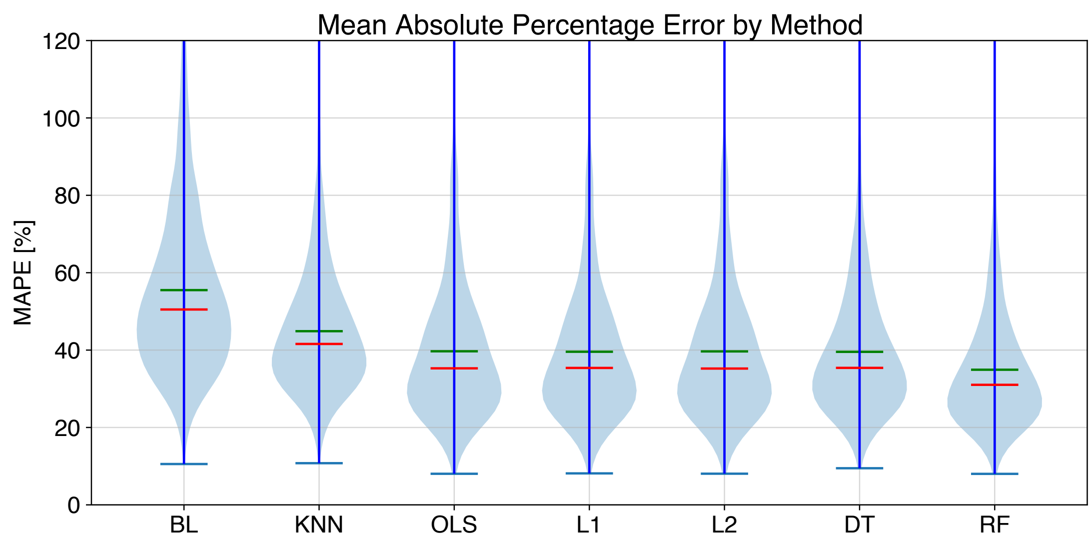
$$H_0 : \hat{\beta}_i = 0, \; H_1 : \hat{\beta} \neq 0$$

Simulation Results – Control and Semisynthetic Data

* One-Sample Prediction Errors:

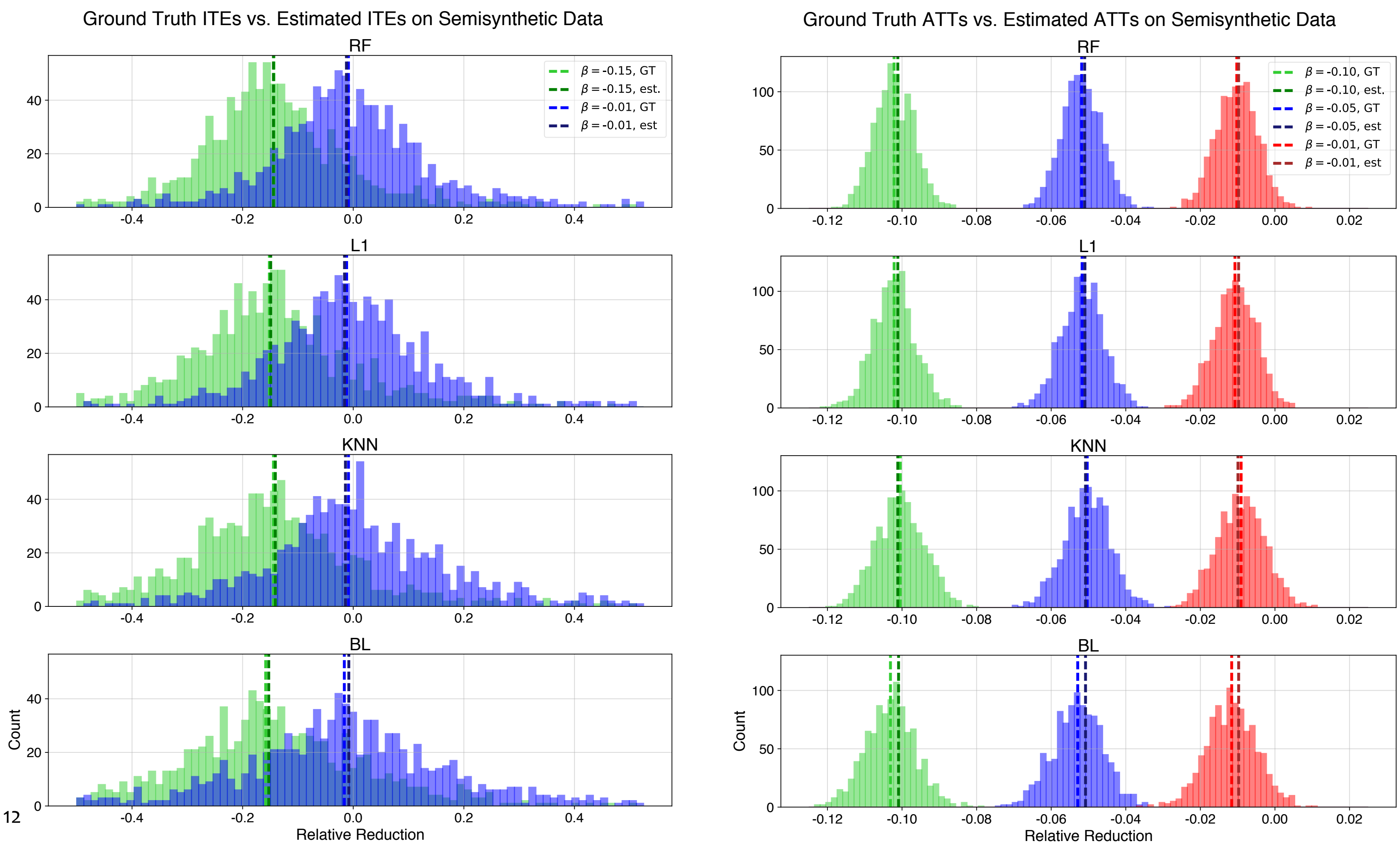


* Mean Absolute Percentage Error:



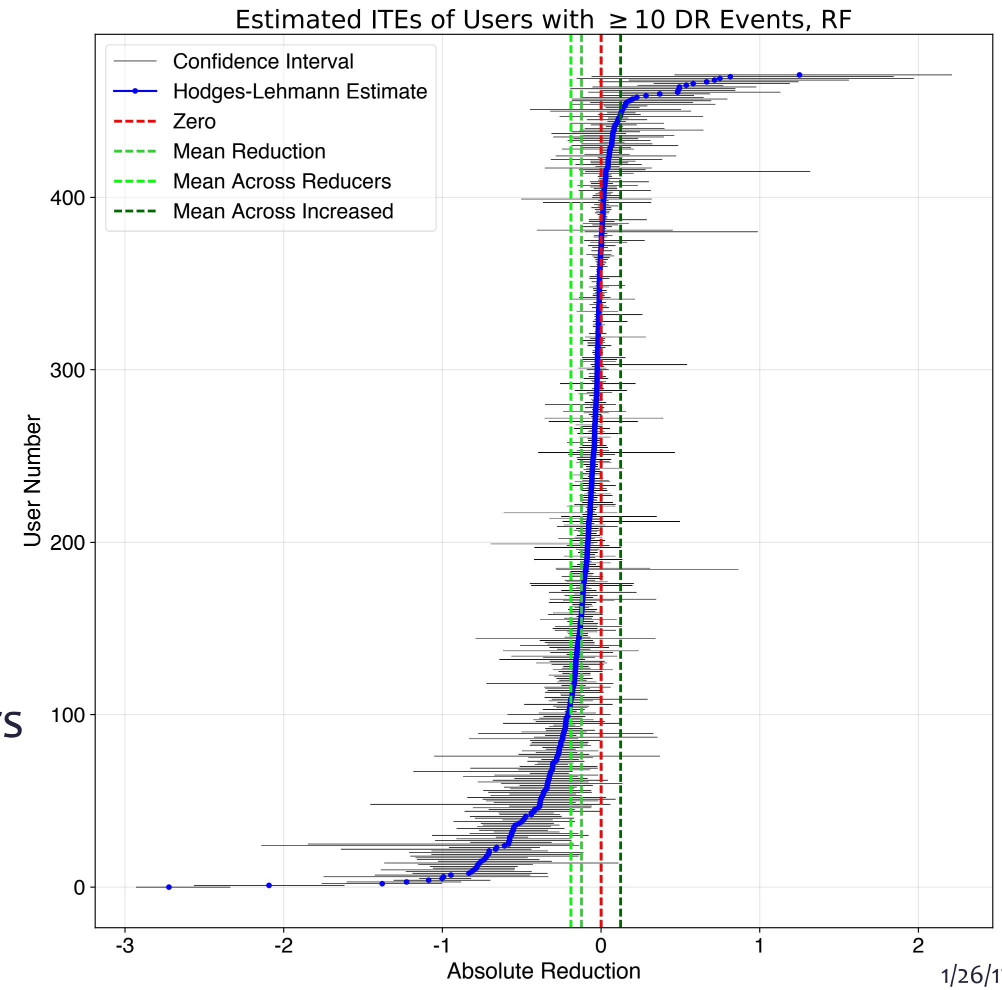
Simulation Results – Control and Semisynthetic Data (cont'd.)

* Simulate user responses on control data, then recover responses



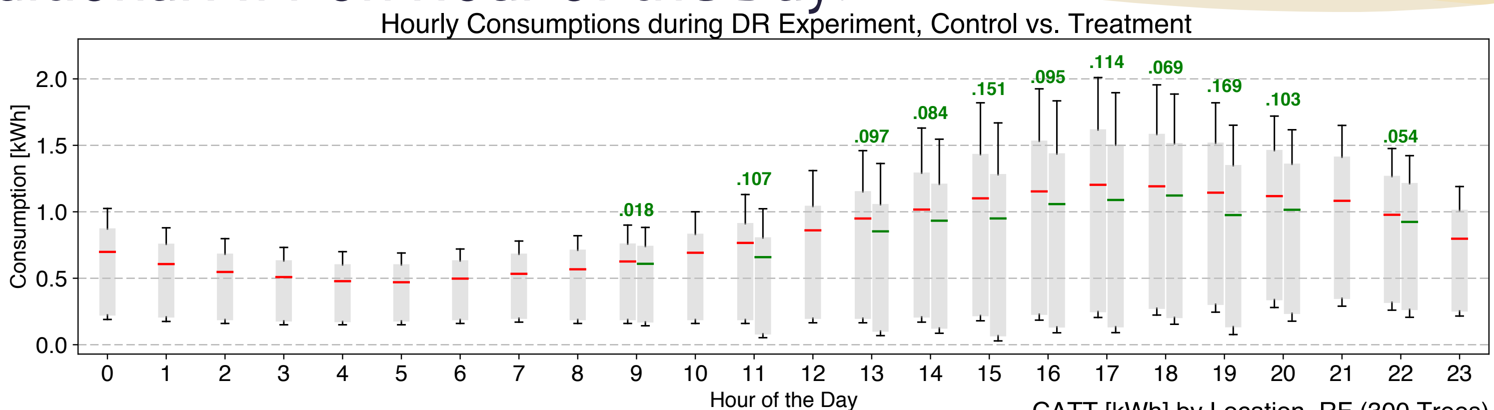
Simulation Results – Treatment Data

* Estimates on 469 users with at least 10 DR events:
* 78.6% of users reduce consumption
* ATT estimate: -0.12 kWh or 10.5% of mean consumption
* Conditional on reducers: -0.19 kWh or 15.3% of mean
* For 90% significance level:
  * 32.8 % significant reducers
  * 45.8% non-significant reducers
  * 19.9% non-significant increasers
  * 1.5% significant increasers

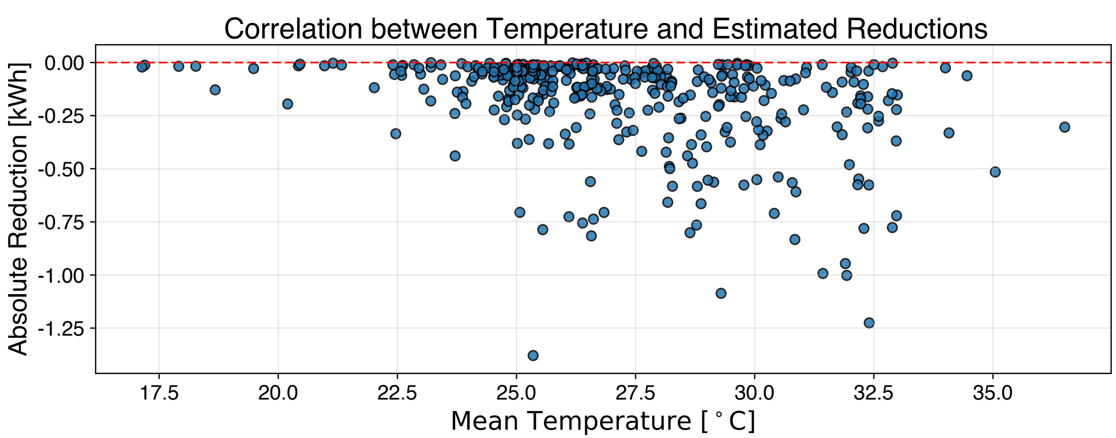


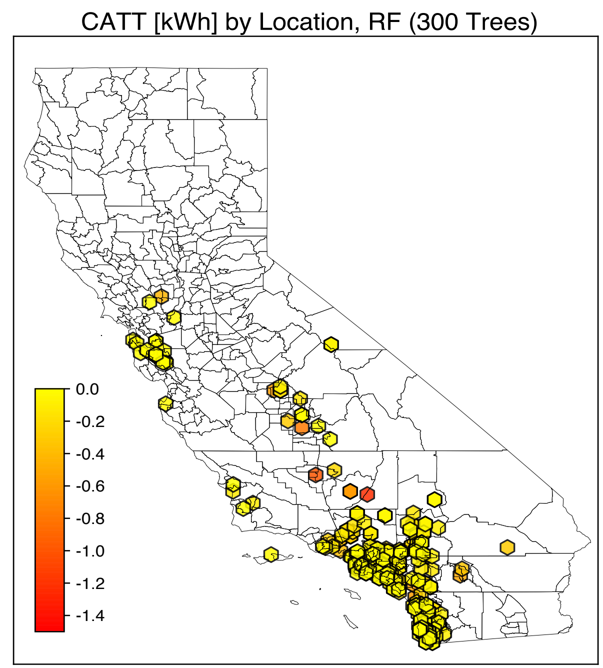
Simulation Results – Treatment Data (cont'd)

* Conditional ATT on Hour of the Day:



* Conditional ATT on Geography:





Discussion & Conclusion

* Estimated Treatment Effects of a Residential Demand Response Program in California
  * 10.5% reduction / 0.12 kWh per event and user
* **Next steps:**
  * Randomized Control Trial (RCT) as an experimental "gold standard" to verify/falsify estimated reductions
  * Analyze heterogeneity of treatment population with respect to:
    * Extent of home automation
    * Social effects (e.g. teams of users, moral suasion)
    * Targeting the "right" users to maximize DRP profit
  * Mechanism Design formulation for DR elicitation
  * Exploration of DRP – Market Interaction: Profit-maximizing bids?

THANK YOU!

QUESTIONS?