How to Use Python and Mathematical Modeling to Better Understand the Impact of Electricity Pricing on Consumption

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PyData NYC 2023

Outline

Overview of the Talk

- Introduce the Problem Space; Define Terminology
- Introduce the Trial and the Dataset
- Mathematical Model
- Data Prep, Cleaning, Processing
- Results

The Background

The Power Grid

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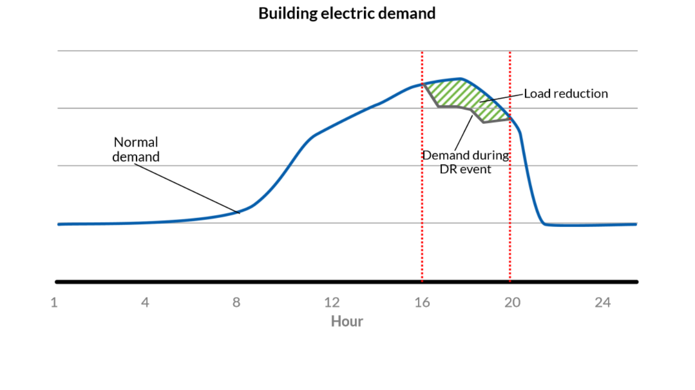
- **System Operators**: Resposible for reliable delivery of electricity to consumers.

Demand Response

(Dynamic) Time of Use Pricing (dToU):

- Assumption 1: Demand can be shifted around.
- Assumption 2: Consumers are price sensitive i.e. there's correlation between demand and price. Causation?



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  As a result, analyses are done on a **population vs a unit**.
- When estimating treatment effect for populations, to remove bias terms, we want samples that behave similarly out of sample.
  As a result, analyses are done on **random samples** of populations.

The Data

Low Carbon London Smart Meter Trial

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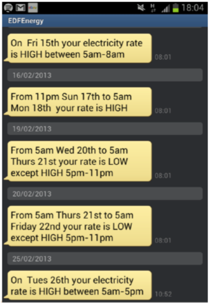
- "Dynamic": Prices were given a day ahead via the Smart Meter In Home Display or text message.



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- dTou price bands vs static pricing model:

dToU Pricing Model	Static Pricing Model
High (67.20 p/kWh)	14.228 p/kWh
Normal (11.76 p/kWh)	14.228 p/kWh
Low (3.99 p/kWh)	14.228 p/kWh

Low Carbon London Smart Meter Trial: Biases?

The trial is double opt-in:

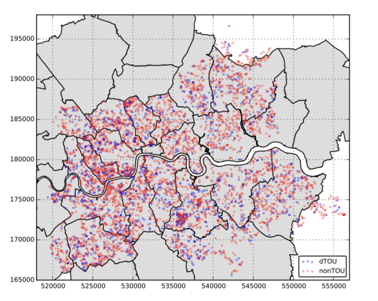
1. Households opt into sharing their data with the trial at all.
2. Some opted into the treatment group: subject to the dToU pricing model in 2013.

Low Carbon London Smart Meter Trial: Biases?

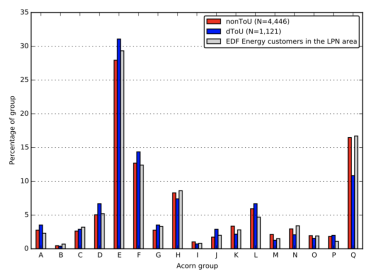
The treatment group was given some incentives:

- A guarantee that they will be reimbursed at the end of trial if they are worse off on the dToU tariff than they would have been on their previous tariff.
- Assurances regarding how many hours would be charged at the high price band.
- £100 for signing up to the dToU tariff.
- Another £50 for staying on the dToU tariff until the end of trial.
- Entry into a prize draw after completion of the post trial survey.

Low Carbon London Smart Meter Trial: Distribution?



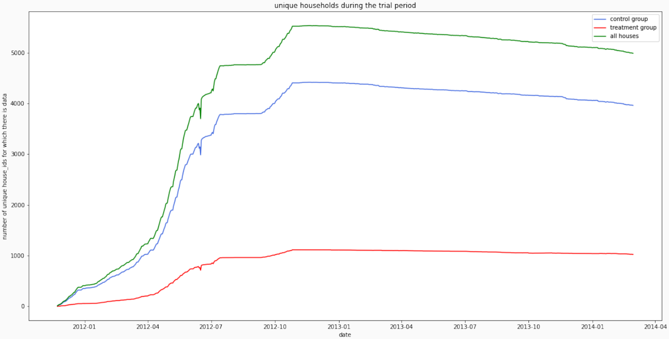
(a) Trial household sample locations overlaid on the borough boundary map of Greater London. Map data from the Greater London Authority. This shows that the treatment and control group were representative samples of Greater London.



(b) The treatment and control groups were also representative socio-economic samples of Greater London.

Low Carbon London Smart Meter Trial: Missing Data

- 2012: Users were still onboarding.
- 2013: Some users dropped out of both the treatment and the control groups
- 5,567 total households participated: 4,500 were in the control group, 1,100 were in the treatment group.



The Math

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- Y_0 and Y_1 are counterfactuals of one another. Both can never be observed at the same time.
  - $Y_i :=$ the outcome of interest for unit i
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- The causal effect of X_i on Y_i is $T = Y_1 - Y_0$, where T stands for Treatment Effect.
- *But what's the issue here?*
- We never observe $Y_1 - Y_0$ for a single unit i. Instead, we observe

$$Y_i = Y_{1i}X_i + Y_{0i}\,(1 - X_i)$$

That is, we observe Y_1 or Y_0 but not both.

Solutions Around FPCI

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Solutions Around FPCI for this Trial

1. Temporal Stability & Causal Transience X
2. Unit Homogeneity X
3. Estimate causal effects for populations rather than units ✓

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- Average Treatment Effect (ATE): $T^\dagger = E\left[Y_1 - Y_0\right]$
- *ATE is treatment effect assuming entire population is treated.*
  - *What's an example?*
  - *Which of the two is more important? But how do we estimate it?*

Estimate Causal Effects for Populations Rather than Units

To make things more complicated, let's make another estimator.

1. $\tilde{T} = E[Y \mid X = 1] - E[Y \mid X = 0]$

Is $\tilde{T}$ a good estimator of T^*? What is it estimating? What change can we make to our population to make this a good estimator?

Estimate Causal Effects for Populations Rather than Units

- Assume your treatment and control group had the same expected baseline behavior, and the same counterfactual expected behavior.

$$E[Y_1 \mid X = 1] = E[Y_1 \mid X = 0]$$
$$E[Y_0 \mid X = 1] = E[Y_0 \mid X = 0]$$

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- Let's revisit

$$\begin{aligned} T^* &= E\left[Y_1 \mid X=1\right] - E\left[Y_0 \mid X=1\right] \\ &= E\left[Y_1 \mid X=1\right] - E\left[Y_0 \mid X=0\right] \end{aligned}$$

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  $$E[Y_0 \mid X = 1] > E[Y_0 \mid X = 0].$$
- ... let's bring back $\tilde{T}$.

Estimate Causal Effects for Populations Rather than Units

So, if we calculated the contrast $\tilde{T} = E[Y \mid X = 1] - E[Y \mid X = 0]$ for this unbalanced group, what would we get?

$$
\begin{aligned}
E\left[Y_1 \mid X = 1\right] - E\left[Y_0 \mid X = 0\right] = & \underbrace{E\left[Y_1 \mid X = 1\right] - E\left[Y_0 \mid X = 1\right]}_{T^*} \\
& + \underbrace{\left\{E\left[Y_0 \mid X = 1\right] - E\left[Y_0 \mid X = 0\right]\right\}}_{\text{Bias}}.
\end{aligned}
$$

(Go to whiteboard and do the rest)

The Analysis

Assume matrix $\alpha^{t \times n_c}$ contains control group data, and $\beta^{t \times n_t}$ contains treatment group data. Where $t = 365 \times 48 = 17520$, n_c is the number of households in the control group and n_t is the number of households in the treatment group.

$$\begin{aligned}
\overline{\beta^m_{2012}} &= a \times \overline{\alpha^m_{2012}} + b \\
\overline{\hat{\beta}^m_{2013}} &= a \times \overline{\alpha^m_{2013}} + b \\
\overline{\Delta \text{treatment}} &= \overline{\beta^m_{2013}} - \overline{\hat{\beta}^m_{2013}}
\end{aligned} \tag{1}$$

Data Prep, Cleaning, Processing

UKPN-LCL-smartmeter-sample.csv	Nov 3, 2020 at 1:44 PM	1 MB	Comma...et (.csv)
Tariffs.xlsx	Jan 4, 2021 at 9:02 PM	235 KB	Microso...k (.xlsx)
Tariffs.csv	Jan 4, 2021 at 9:02 PM	371 KB	Comma...et (.csv)
tariffs_csv.csv	Jan 4, 2021 at 9:02 PM	371 KB	Comma...et (.csv)
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Power-Networks-LCL-June2015(withAcornGps)v2_167.csv	Aug 20, 2015 at 1:09 PM	68.5 MB	Comma...et (.csv)
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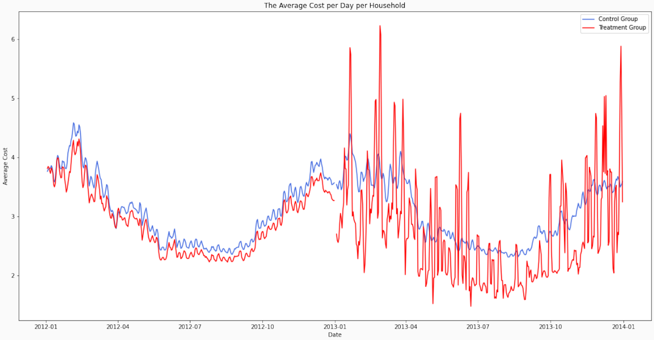

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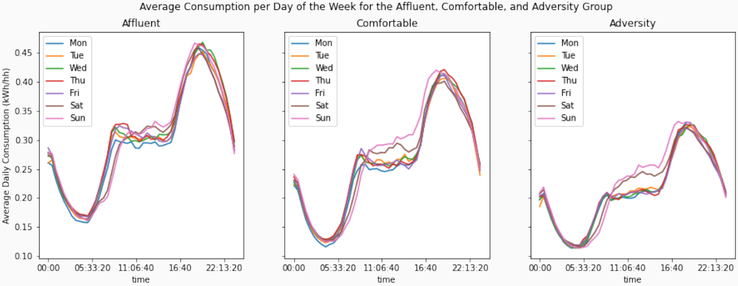

The Conclusion

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- Questions to ask before analysis:
    - How was the data collected?
    - What biases are present?
    - How does that impact your analysis and results?

Thank You

- https://github.com/sabanejad
- https://www.linkedin.com/in/sabanejad/

Appendix

Potential Outcomes Framework (Rubin-Neyman Causal Model)

Each household x_i has two potential outcomes:

- $Y_0(x_i)$ is the potential outcome had the unit not been treated (static pricing model): "control outcome"
- $Y_1(x_i)$ is the potential outcome had the unit been treated (dToU pricing model): "treated outcome"

- Conditional average treatment effect for unit i :

$$\mathrm{CATE}(x_i) = \mathbb{E}_{Y_1 \sim p(Y_1|x_i)}[Y_1 \mid x_i] - \mathbb{E}_{Y_0 \sim p(Y_0|x_i)}[Y_0 \mid x_i]$$

- Average Treatment Effect:

$$ATE := \mathbb{E}[Y_1 - Y_0] = \mathbb{E}_{x \sim p(x)}[\mathrm{CATE}(x)]$$

Mathematical Model

- Fundamental Problem of Causal Inference: Both outcomes can't be observed for the same household x_i.
  - Observed factual outcome:

$$y_i = t_i Y_1 (x_i) + (1 - t_i) Y_0 (x_i)$$

  - Unobserved counterfactual outcome:

$$y_i^{CF} = (1 - t_i) Y_1 (x_i) + t_i Y_0 (x_i)$$

- Solution? Approximate the counterfactual eg close enough to random sample: minimum wage problem, NJ and east PA, Card & Krueger, 1994.

David Card minimum wage paper:

https://davidcard.berkeley.edu/papers/njmin-aer.pdf

LCL Experiment https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households