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

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November 2, 2023

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, Lessons Learned, Conclusion

The Background

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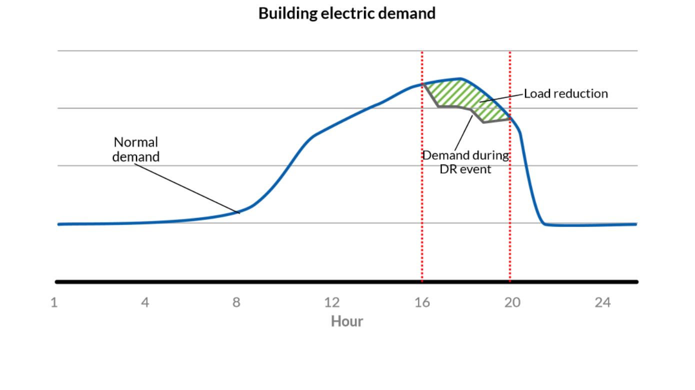
- **System Operators**: Resposible for reliable delivery of electricity to consumers.

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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  - $Y_1 :=$ the value of Y for $X = 1$ (treated unit)
- Y_0 and Y_1 are **counterfactuals** of one another. We observe Y_1 or Y_0 but not both at the same time.

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  $\implies$ 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.
  $\implies$ analyses are done on **random samples** of populations.

The Data

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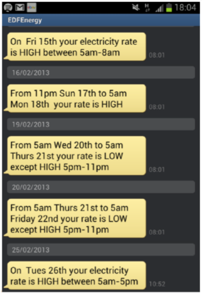
- "Dynamic": Prices were given a day ahead via the Smart Meter In Home Display or text message.



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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:

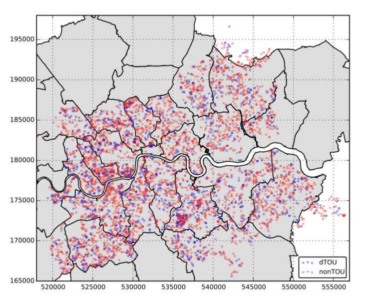
1. Households opt into sharing their data with the trial at all.
2. Some opted into the treatment group: subject to the dToU pricing model in 2013.

Low Carbon London Smart Meter Trial: Biases?

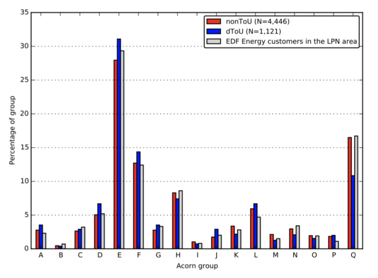
The treatment group was given some incentives:

- 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?



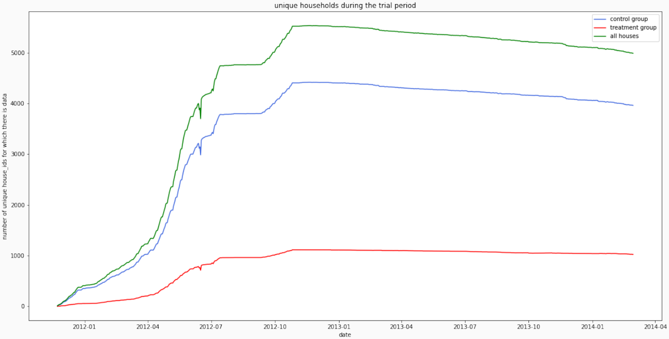
(a) Trial household sample locations overlaid on the borough boundary map of Greater London. Map data from the Greater London Authority. This shows that the treatment and control group were representative samples of Greater London.



(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.



Treatment vs Control Group Baselines

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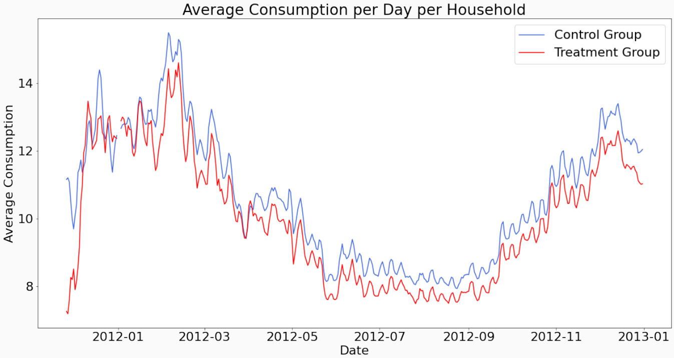
- What are some reasons the baselines might differ given what we know?
    - price sensitive group opted in
    - low consuming group opted in
    - those households are flexible time-wise: particular jobs, hours, etc.

Treatment vs Control Group Baselines

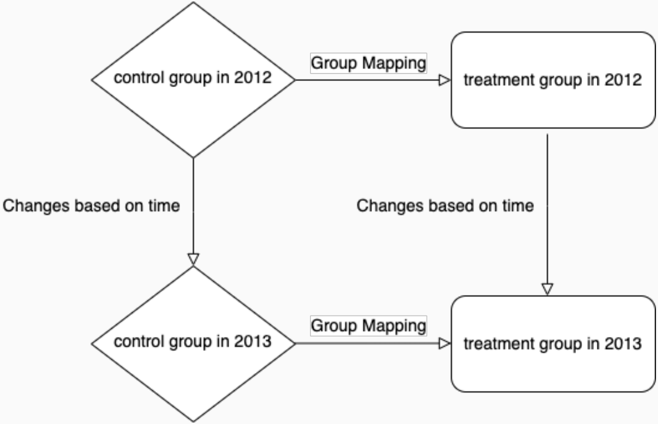


$\Longrightarrow$ the two groups don't have the same baseline electricity consumption patterns.

Treatment vs Control Group Baselines

$$\begin{array}{ccc}
f_{2012}\left(\theta_{tr}, T, t\right) & \xrightarrow{h(t)} & f^{*}_{2013}\left(\theta_{tr}, T, t\right) \\
g\left(\theta_{c}\right)\uparrow & & g\left(\theta_{c}\right)\uparrow \\
f_{2012}\left(\theta_{c}, T, t\right) & \xrightarrow{h(t)} & f_{2013}\left(\theta_{c}, T, t\right)
\end{array}$$

Treatment vs Control Group Baselines



Treatment Effective?

If we look at percent change without normalizing the baselines the treatment was effective.

The Math

Mathematical Model

Consider the following segmentation of the data.

- $\alpha_y :=$ control group's consumption matrix during year y
- $\beta_y :=$ treatment group's consumption matrix during year y

Mathematical Model

Year	Control Group	Treatment Group
2011	α_{2011}	β_{2011}
2012	α_{2012}	β_{2012}
2013	α_{2013}	β_{2013}*
2014	α_{2014}	β_{2014}

Mathematical Model

$$\begin{aligned} \alpha_{2012} X &= \beta_{2012} \\ \alpha_{2013} X &= \hat{\beta}_{2013} \\ \Delta \text{treatment} &= \beta_{2013} - \hat{\beta}_{2013} \end{aligned} \tag{1}$$

Other Clustering?

I used different clustering methods to cluster houses in this data set based on the control group's consumption pre-intervention: k-means clustering, PCA3, TSNE4. I also tried clustering on the frequency responses which I found fast Fourier trans- form. PCA, TSNE, and Agglomerative clustering on the resulting data set was also inconclusive. This is reason for sticking to the pre-existing socio-economic clusters.

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 the number of households in the treatment group.

$$\begin{aligned} \overline{\beta^m_{2012}} &= a \times \overline{\alpha^m_{2012}} + b \\ \overline{\hat{\beta}^m_{2013}} &= a \times \overline{\alpha^m_{2013}} + b \\ \overline{\Delta\text{treatment}} &= \overline{\beta^m_{2013}} - \overline{\hat{\beta}^m_{2013}} \end{aligned} \tag{2}$$

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_152.csv	Aug 20, 2015 at 1:02 PM	68.8 MB	Comma...et (.csv)
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Power-Networks-LCL-June2015(withAcornGps)v2_150.csv	Aug 20, 2015 at 1:01 PM	68.7 MB	Comma...et (.csv)
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Power-Networks-LCL-June2015(withAcornGps)v2_139.csv	Aug 20, 2015 at 12:56 PM	68.7 MB	Comma...et (.csv)
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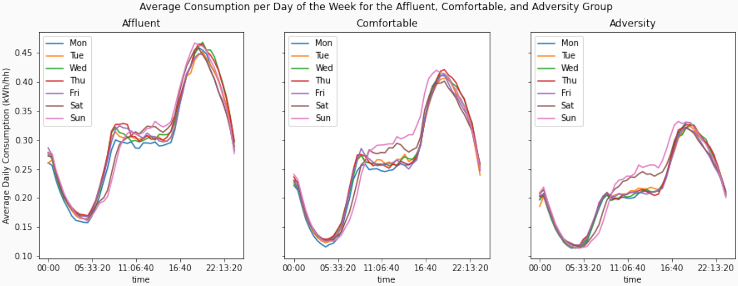

The Conclusion

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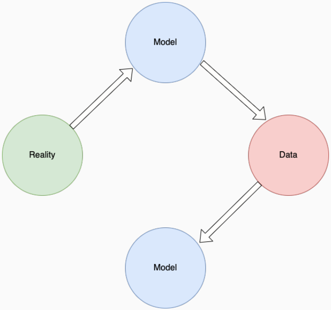

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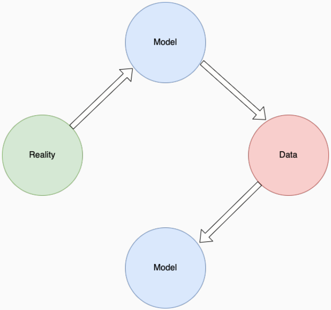

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  - What biases are present?
  - How does that impact your analysis and results?

Thank You

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