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

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PyData NYC 2023

Overview of the Talk

- Introduce the Problem Space; Define Terminology

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- Introduce the Trial and the Dataset

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- Results, Lessons Learned, Conclusion

The Background

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

Demand Response

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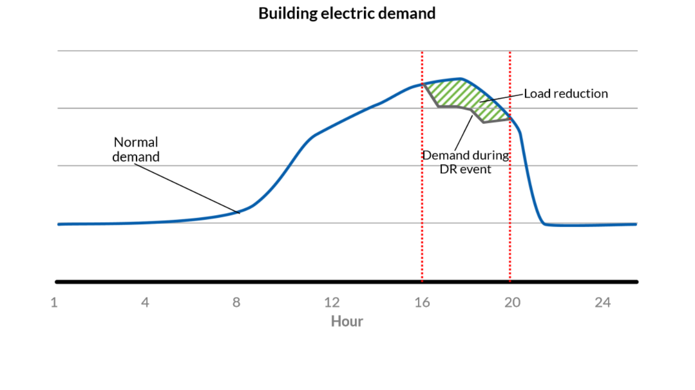

Causal Inference

What is causal inference and treatment effect in laymen terms; what is a treatment. rethink ordering of the next few slides

Other Challenges with Causal Inference

- It's difficult to estimate the treatment effect for a unit.

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- It's difficult to estimate the treatment effect for a unit.
  $\implies$ 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.

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    - $T = Y_1 - Y_0 :=$ the treatment effect
- Y_0 and Y_1 are **counterfactuals** of one another. We observe **only** Y_1 or Y_0, but not both at the same time.

Solutions Around FPCI

1. Temporal Stability & Causal Transience

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Solutions Around FPCI for this Trial

1. Temporal Stability & Causal Transience X
2. Unit Homogeneity X
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The Data

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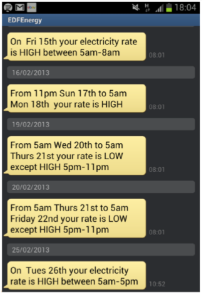
- "Dynamic": Prices were given a day ahead via the Smart Meter In Home Display or text message.



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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

Additional Features: Discrete Socio-Economic Categories

discrete socio-economic feature per household included in the data

Low Carbon London Smart Meter Trial: Biases?

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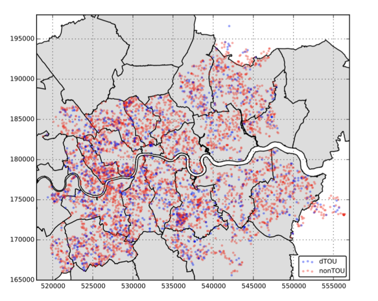
1. Households opt into sharing their data with the trial at all.
2. Some opted into the treatment group: subject to the dToU pricing model in 2013.

Low Carbon London Smart Meter Trial: Biases?

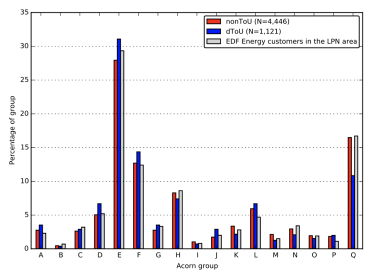
The treatment group was given some incentives:

- 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?



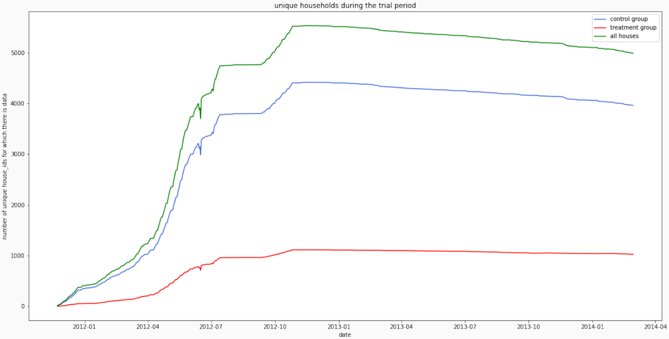
(a) Trial household sample locations overlaid on the borough boundary map of Greater London. Map data from the Greater London Authority. This shows that the treatment and control group were representative samples of Greater London.



(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
- ~5,600 total households participated: ~4,500 were in the control group, ~1,100 were in the treatment group.



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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.

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

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

Dimenstionality Analysis

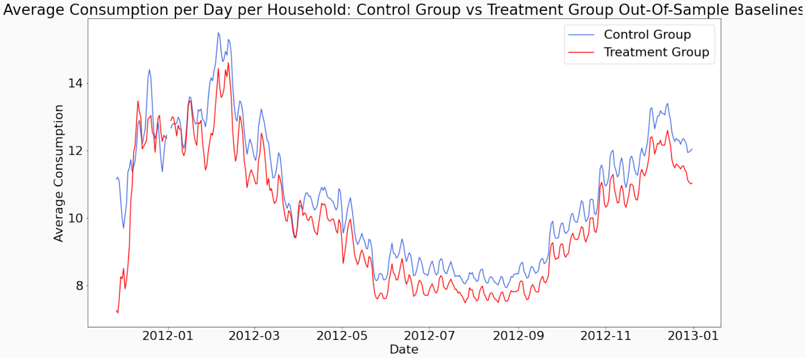
Here?

Naive Model

If we didn't know about all these biases, we *could* use control group in 2013 as the counterfactual estimate for treatment group in 2013.

$$\begin{aligned} \hat{\beta}_{2013} &\approx \alpha_{2013} \\ T &= \beta_{2013} - \hat{\beta}_{2013} \\ &= \beta_{2013} - \alpha_{2013} \end{aligned} \tag{2}$$

Treatment vs Control Group Baselines

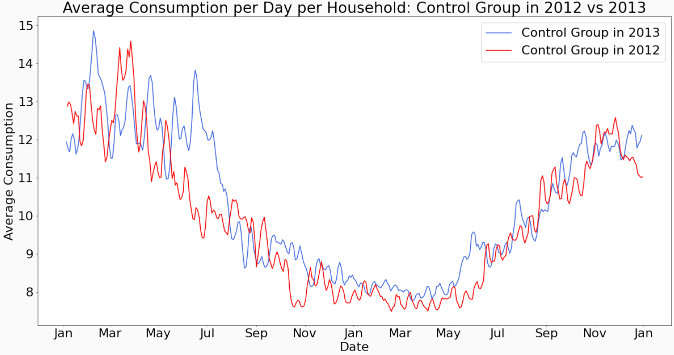


$\Longrightarrow$ the two groups don't have the same baseline electricity consumption patterns.

Sophisticated Naive Model

now use treatment last year

Changes from Time: 2012 vs 2013



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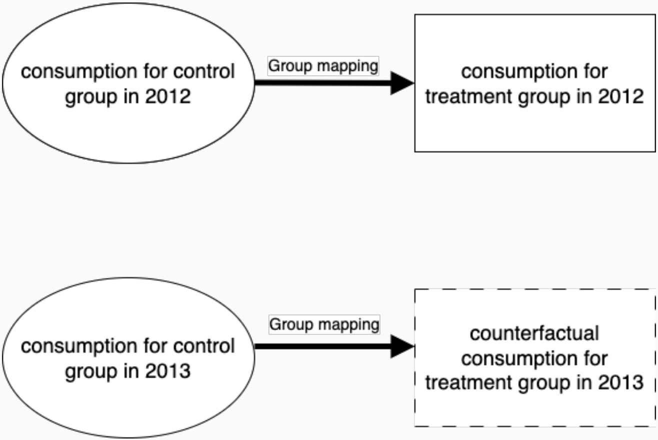

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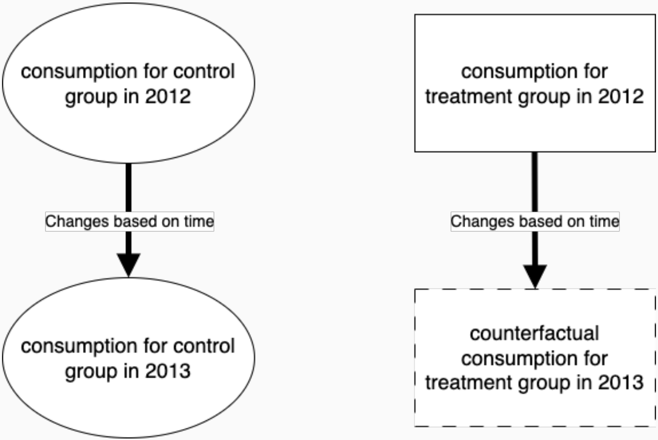

Treatment Effective?

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

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 number of households in the treatment group.

$$
\begin{aligned}
\overline{\beta^m_{2012}} &= a \times \overline{\alpha^m_{2012}} + b \\
\overline{\hat{\beta}^m_{2013}} &= a \times \overline{\alpha^m_{2013}} + b \\
\overline{\Delta \text{treatment}} &= \overline{\beta^m_{2013}} - \overline{\hat{\beta}^m_{2013}}
\end{aligned} \tag{3}
$$

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)
Power-Networks-LCL-June2015(withAcornGps)v2_168.csv	Aug 20, 2015 at 1:09 PM	64.7 MB	Comma...et (.csv)
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Power-Networks-LCL-June2015(withAcornGps)v2_166.csv	Aug 20, 2015 at 1:09 PM	68.7 MB	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)
Power-Networks-LCL-June2015(withAcornGps)v2_149.csv	Aug 20, 2015 at 1:00 PM	68.8 MB	Comma...et (.csv)
Power-Networks-LCL-June2015(withAcornGps)v2_148.csv	Aug 20, 2015 at 1:00 PM	68.8 MB	Comma...et (.csv)
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Data Prep, Cleaning, Processing

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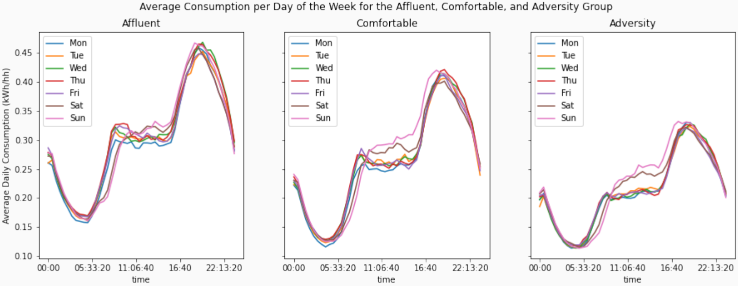

The Conclusion

Lessons Learned

- KYD: know your data: learn how it was collected, its biases, shortcomings, feature space, problem space.

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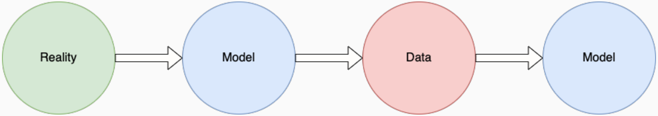
- KYD: know your data: learn how it was collected, its biases, shortcomings, feature space, problem space.
- Before diving into fitting a model to your data, it's important to base your analysis on some mathematical model



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- How to break down your data to match the mathematical model at hand.
- 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/