

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

Saba Nejad

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PyData NYC 2023

Hi! I'm Saba. Thank you for coming to my talk.

My name is Saba. I'm a Data Engineer at Point72. Today, I'll be walking you through part of my master's thesis that I worked on and defended two years ago at MIT.



Goals for this talk

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 - how it was collected
 - its biases
 - dimensionality, fill-rate, etc.

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- Before trying to fit a model to your data, you should have a mathematical model rooted in the real world.

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- the thinking behind the mathematical framing of the problem.
- the analysis based on the particular dataset and mathematical model.
- results, takeaways, lessons learned.

Useful Details about the Problem Space

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- Electricity is unique in that its **storage is prohibitively costly**.
- As a result, **supply must meet demand** at all times.
- If demand exceeds supply, there will be a power outage.
- Power outages are extremely costly and we try to prevent them as much as possible.

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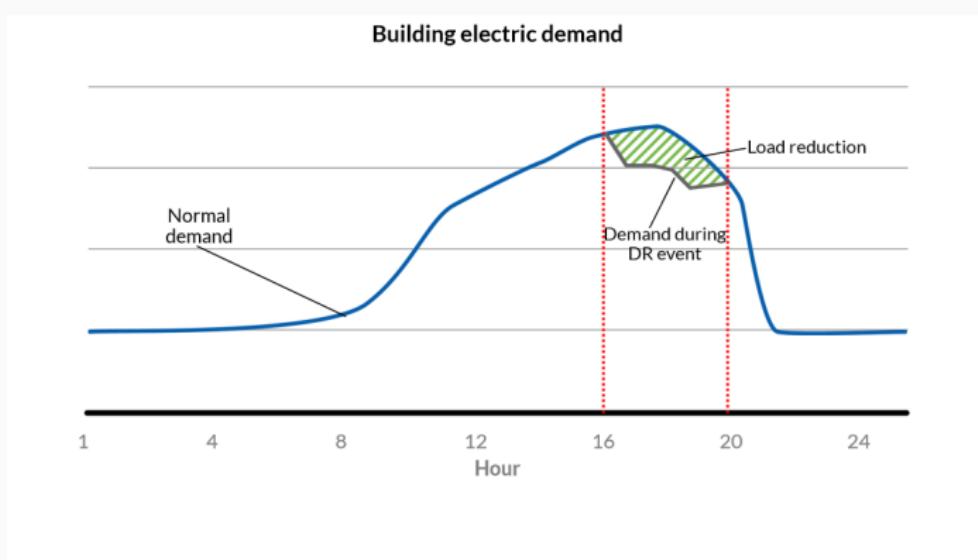
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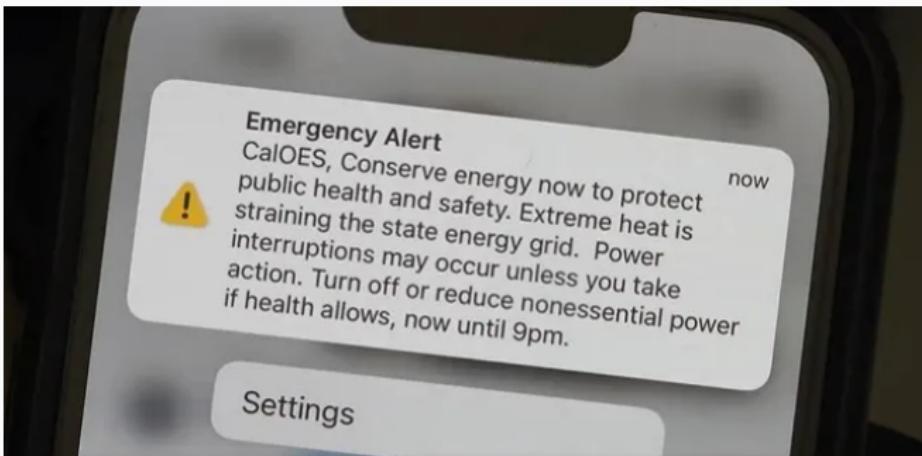
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- This unique feature of electricity, poses a **challenge**.
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- To prevent a power outage, we need close to real-time methods to lower demand.
- **Demand Response** is one such method.

Demand Response visual example



Demand Response is a tragedy of the commons issue.



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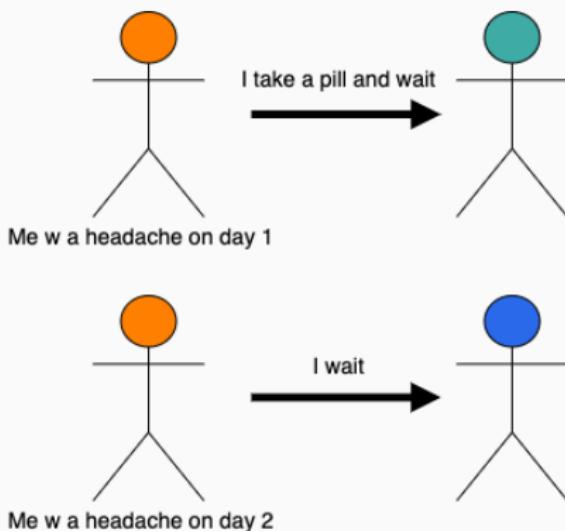
- Assumption 1: Demand can be shifted around.
- Assumption 2: Consumers are price sensitive i.e. they will respond to price incentives.
- Two pricing models:
 - Time of Use Pricing
 - Dynamic Time of Use Pricing

Repeat

There is a pricing model, called **Dynamic Time of Use Pricing**, that uses price incentives to lower demand on the grid and prevent a power outage.

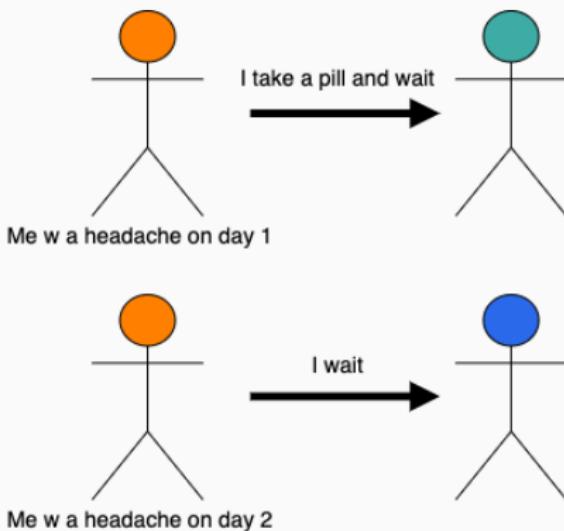
Understanding causality and some useful terminology

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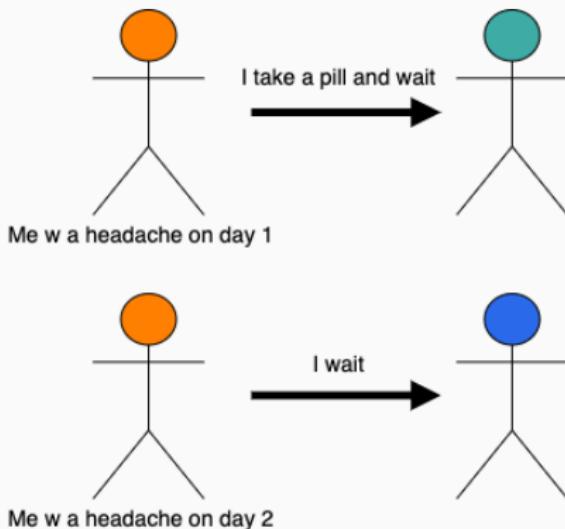
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Understanding causality and some useful terminology

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- What is a treatment
- What is the counterfactual



The Fundamental Problem of Causal Inference (FPCI)

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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
3. Estimate causal effects for populations rather than units ✓

Random samples of populations are studied to estimate treatment effects.

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- When estimating treatment effect for populations, to remove bias terms, we want groups that behave similarly out of sample.
 \Rightarrow analyses are done on **random samples** of populations.

What have we learned and where are we headed?

now we have some mathematical tools in our toolbox to study causality and estimate treatment effects. we know a bit about the pricing model in this trial. now let's go learn more about the trial and the data

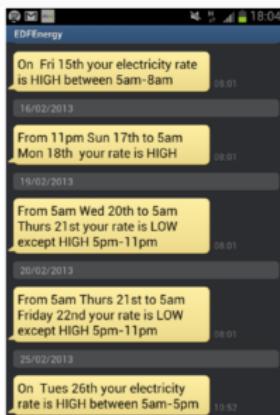
The Details of the Trial Studied

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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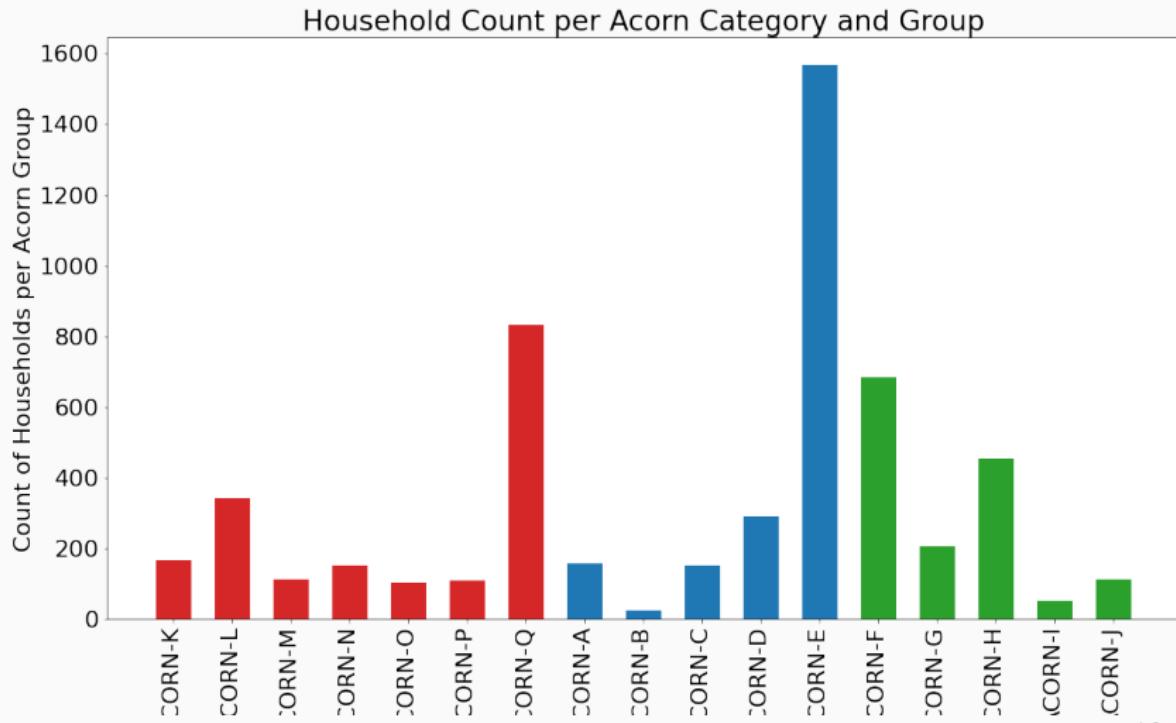
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- Treatment took place in the calendar year 2013.
- Readings were taken at half hourly intervals.
- dToU price bands vs static pricing model:

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

Label	Acorn group	Acorn category
A	Wealthy executives	Wealthy achievers
B	Affluent greys	Wealthy achievers
C	Flourishing families	Wealthy achievers
D	Prosperous professionals	Urban prosperity
E	Educated urbanites	Urban prosperity
F	Aspiring singles	Urban prosperity
G	Starting out	Comfortably off
H	Secure families	Comfortably off
I	Settled suburbia	Comfortably off
J	Prudent pensioners	Comfortably off
K	Asian communities	Moderate means
L	Post industrial families	Moderate means
M	Blue collar roots	Moderate means
N	Struggling families	Hard pressed
O	Burdened singles	Hard pressed
P	High rise hardship	Hard pressed
Q	Inner city adversity	Hard pressed

Additional Features: Two Levels of Discrete Socio-Economic Categories



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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.

The two groups were not biased geographically

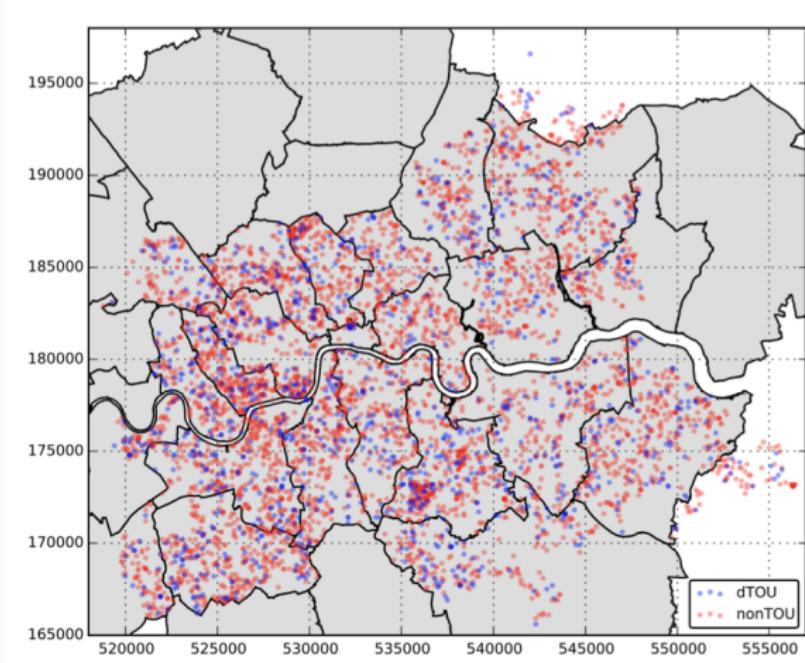
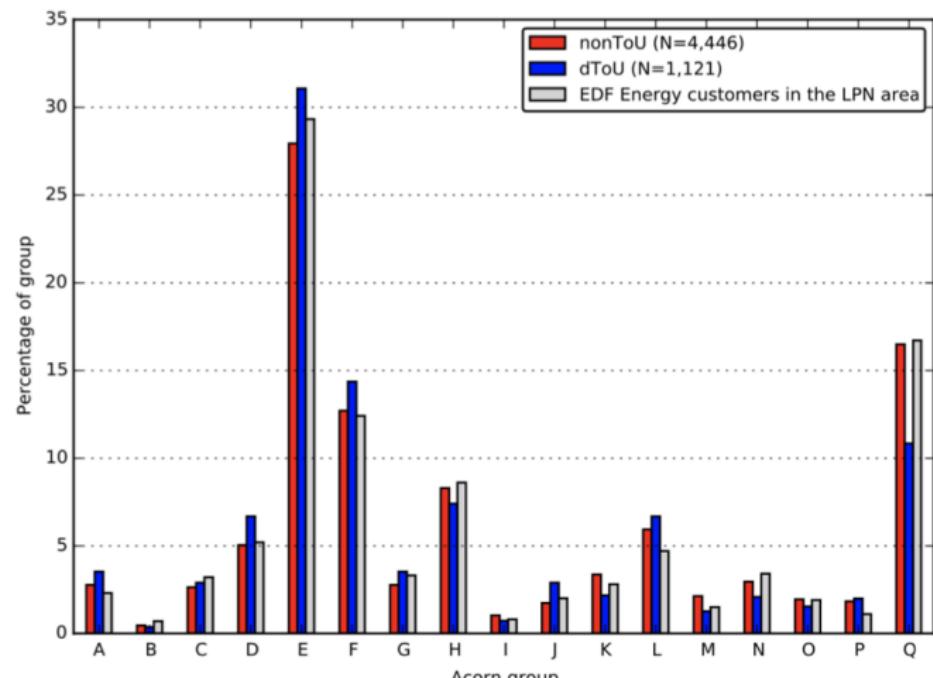


Figure 1: Trial household sample locations overlaid on the borough boundary map of Greater London. This shows that the treatment and control group were representative samples of Greater London.

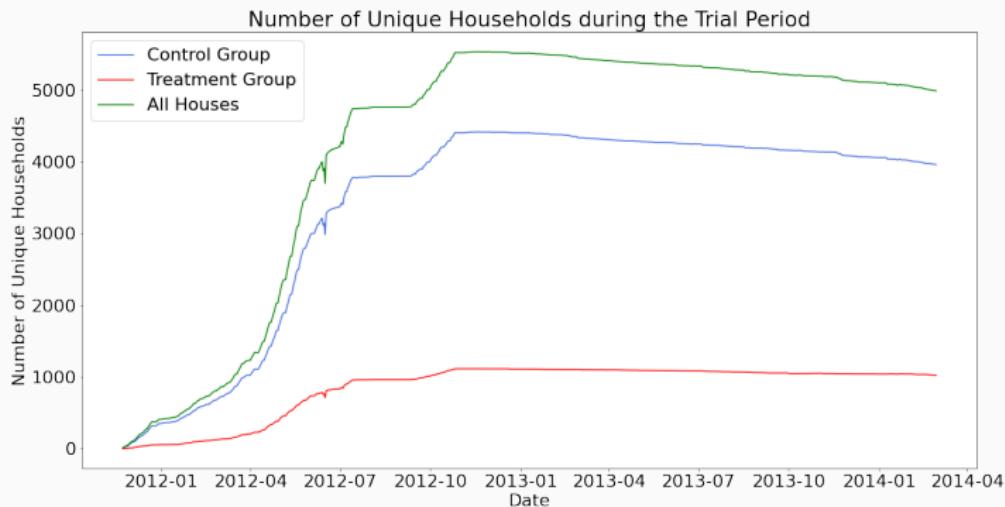
The two groups were not biased socio-economically



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

Dimensionality Analysis: Treatment & Control Group Matrices

$$\alpha_y = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n_c} \\ a_{21} & a_{22} & \cdots & a_{2n_c} \\ \vdots & \vdots & \ddots & \vdots \\ a_{t1} & a_{t2} & \cdots & a_{tn_c} \end{bmatrix} \quad \beta_y = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n_t} \\ b_{21} & b_{22} & \cdots & b_{2n_t} \\ \vdots & \vdots & \ddots & \vdots \\ b_{t1} & b_{t2} & \cdots & b_{tn_t} \end{bmatrix}$$

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($t = 365 \times 48 = 17,520$ for 2012 and 2013).

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n_c is the number of households in the control group; n_t is the number of households in the treatment group.

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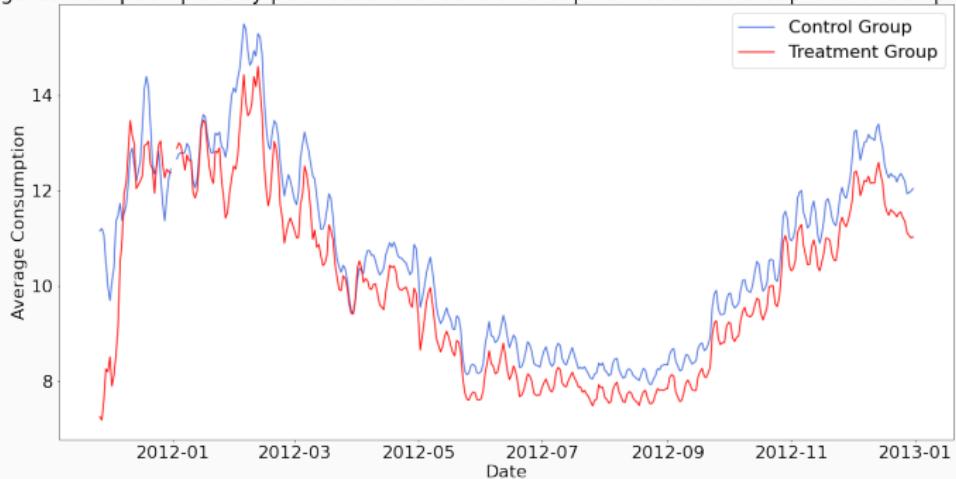
Naive Model: Use Treatment Group in 2013 as Counterfactual

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.

$$\begin{aligned}\hat{\beta}_{2013} &\approx \alpha_{2013} \\ T &= \beta_{2013} - \hat{\beta}_{2013} \\ &= \beta_{2013} - \alpha_{2013}\end{aligned}\tag{1}$$

Treatment vs Control Group Baselines

Average Consumption per Day per Household: Control Group vs Treatment Group Out-Of-Sample Baselines



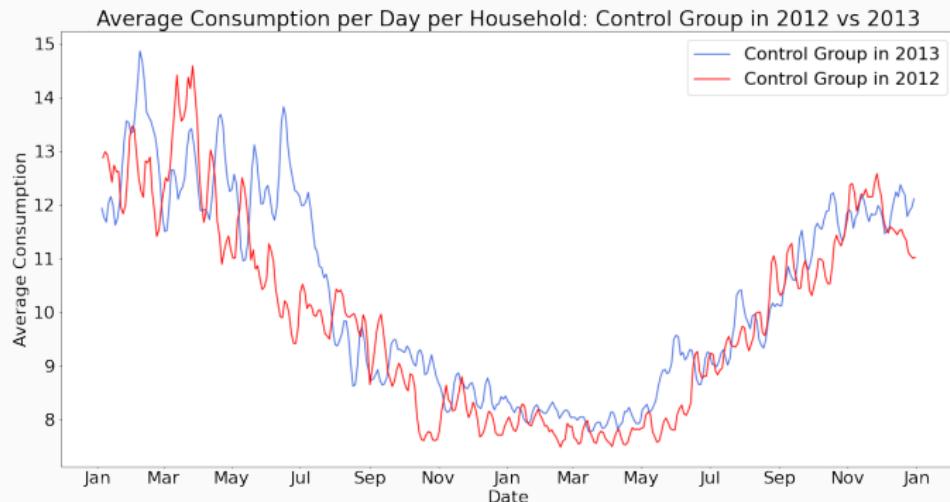
⇒ the two groups don't have the same baseline electricity consumption patterns.

Sophisticated Naive Model

Let's instead use treatment group in 2012 as the counterfactual estimate for treatment group in 2013.

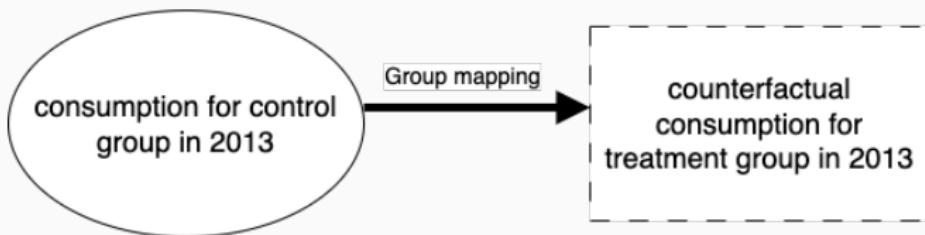
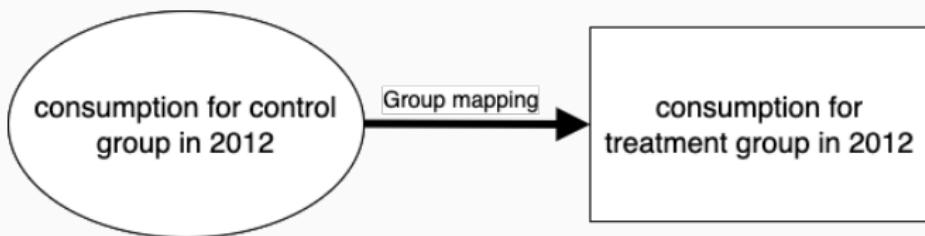
$$\begin{aligned}\hat{\beta}_{2013} &\approx \beta_{2012} \\ T &= \beta_{2013} - \hat{\beta}_{2013} \\ &= \beta_{2013} - \beta_{2012}\end{aligned}\tag{2}$$

Changes from Time: 2012 vs 2013

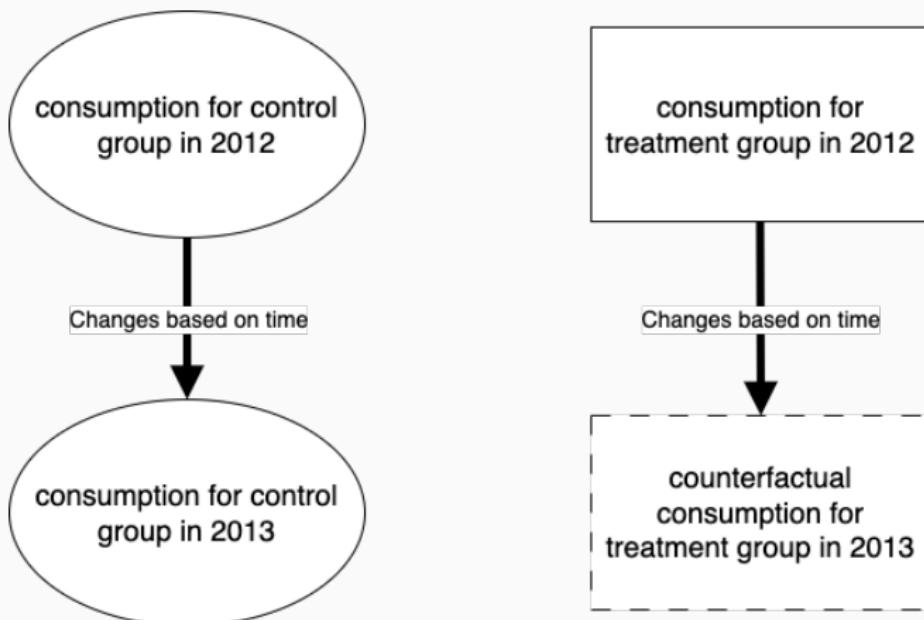


⇒ Things changed between the two years even for the control group.

Treatment vs Control Group Baselines



Treatment vs Control Group Baselines



Mathematical Model: Using Group Mapping

$$\begin{aligned}\alpha_{2012}X &= \beta_{2012} \\ \alpha_{2013}X &= \hat{\beta}_{2013} \\ \Delta\text{treatment} &= \beta_{2013} - \hat{\beta}_{2013}\end{aligned}\tag{3}$$

The Analysis

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	377 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)
 Power-Networks-LCL-June2015(withAcornGps)v2_167.csv		Aug 20, 2015 at 1:09 PM	68.5 MB	Comma...et (.csv)
 Power-Networks-LCL-June2015(withAcornGps)v2_166.csv		Aug 20, 2015 at 1:09 PM	68.7 MB	Comma...et (.csv)
 Power-Networks-LCL-June2015(withAcornGps)v2_165.csv		Aug 20, 2015 at 1:08 PM	68.8 MB	Comma...et (.csv)
 Power-Networks-LCL-June2015(withAcornGps)v2_164.csv		Aug 20, 2015 at 1:08 PM	68.5 MB	Comma...et (.csv)
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 Power-Networks-LCL-June2015(withAcornGps)v2_154.csv		Aug 20, 2015 at 1:03 PM	69 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)
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 Power-Networks-LCL-June2015(withAcornGps)v2_142.csv		Aug 20, 2015 at 12:57 PM	68.8 MB	Comma...et (.csv)
 Power-Networks-LCL-June2015(withAcornGps)v2_141.csv		Aug 20, 2015 at 12:57 PM	68.8 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)
 Power-Networks-LCL-June2015(withAcornGps)v2_138.csv		Aug 20, 2015 at 12:55 PM	68.9 MB	Comma...et (.csv)

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2. second contains house_id (str), acorn (str), acorn_group (str).
3. third is the tariff file contains date_time (datetime), price per designation for that hh (float).

Data Prep, Cleaning, Processing

Name	Date Modified	Size	Kind
tariffs.gzip	Mar 29, 2021 at 9:51 PM	108 KB	gzip compressed archive
total_acorn.gzip	May 16, 2021 at 4:30 PM	30 KB	gzip compressed archive
total_usage_2011.gzip	Mar 2, 2021 at 12:18 AM	628 KB	gzip compressed archive
total_usage_2012.gzip	Apr 26, 2022 at 7:30 PM	185.2 MB	gzip compressed archive
total_usage_2013.gzip	Apr 26, 2022 at 10:28 AM	298.9 MB	gzip compressed archive
total_usage_2014.gzip	Apr 26, 2022 at 10:28 AM	20.9 MB	gzip compressed archive
total_usage.gzip	Mar 2, 2021 at 12:16 AM	549.6 MB	gzip compressed archive

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 transform. 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.

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.

$$\begin{aligned}\overline{\beta_{2012}^m} &= a \times \overline{\alpha_{2012}^m} + b \\ \overline{\hat{\beta}_{2013}^m} &= a \times \overline{\alpha_{2013}^m} + b \\ \overline{\Delta \text{treatment}} &= \overline{\beta_{2013}^m} - \overline{\hat{\beta}_{2013}^m}\end{aligned}\tag{4}$$

The Conclusion

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What Did We Learn?

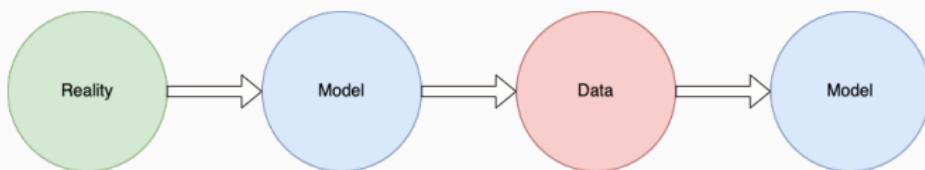
- A little bit about electricity markets?
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- How to break down your data to match the mathematical model at hand.
- Questions to ask before analysis:
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 - What biases are present?
 - How does that impact your analysis and results?

Takeaways

- 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



Thank You! Questions?

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