An Empirical Analysis On Disparate Impacts of the London 2012 Olympics

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Background

Motivation

Studies have been done extensively on the economic impact of **London Olympics** overall—there lacks literature targeting the more intangible aspects of its **various boroughs**

Focus

London Olympics targeted specifically the so-called **"growth boroughs"**. We seek primarily to examine and investigate whether or not this strategy has been successful or have yielded unintended short and long term consequences

Data

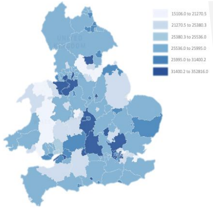
GDP per capita, ethnic distribution, leisure-related data, etc. in **time-series (~2000-2018)** and **per-region (UK boroughs + international cities)** format

Obtaining Net Effect of Olympics

Constructing Control Group

Local Trends

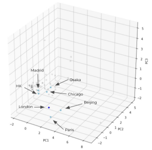
Obtain Non-London UK borough data (GDP per capita in pounds shown to the right)



International Trends

Use **KNN** to obtain the most similar international city to London to put alongside UK boroughs

PCA Representation

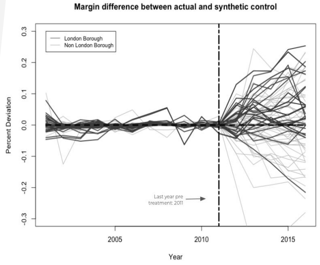


Estimating True Average Treatment Effect (ATE) of Olympics

Model: Lasso-based Modified Synthetic Control

Using members of the Control Group, construct a synthetic control counterfactual for the GDP per capita of London boroughs, and obtain net ATE for periods post Olympics in order to establish causality.

Graphics Below: Shows the marginal difference between the actual GDP per capita of UK boroughs with the predicted GDP per capita



Net Present Value (NPV) of panel ATE:

Using the Annuity formula and the corresponding interest rate, calculate the NPV of all net ATE in the future

Back Attribution to Borough Characteristic

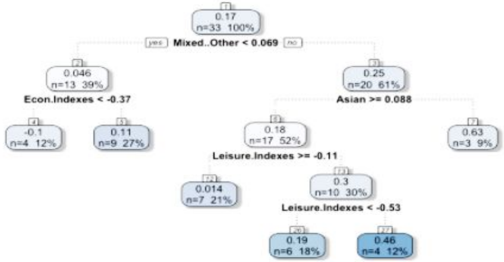
Machine Learning based Attribution

Using the final NPV value obtained as our dependent variable, we employed standard machine learning algorithms, including a **Decision Tree**, in an attempt to understand what explains the **difference of ATE across boroughs.** Economic and Leisure indexes were constructed using PCA on relevant characteristic of the borough

Key Preliminary Insights:

1. Certain protected classes such as Asians does not seem to receive equal degrees of benefit from the Olympics

Decision Tree Using Aggregated ATE



We also further examined the potential **non-stationarity** that exists along how the various characteristics affected both the immediate and long term development of these areas. Here, we used **time-based Linear Regression**

Key Preliminary Insights:

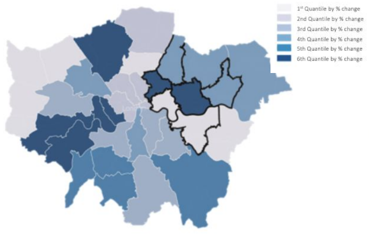
1. Cities with lower economic indexes and higher leisure indexes benefited in the short term, however the trend reversed later on
2. GDP/capita growth in general show a positive trend over the years

Time based Variable Importance

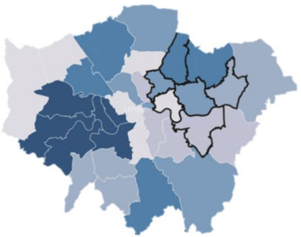
Insights and Recommendations

Deep Dive Comparison

2012 GDP per capita margin **[Short Term]**



GDP NPV per capita margin (2012-2015) **[Long Term]**



Note: Host cities are bolded

We can clearly see that the Host city only obtained short term gain from the comparison. **Thus, we pose that the impact of Olympics is likely more a multiplier to the currently already well-off and fast developing cities in London (centered in West London)** that can take advantage of the intangible impacts of Olympics (e.g. increasing awareness and better infrastructure)

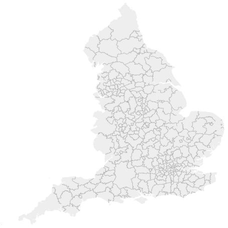
Recommendation: invest in changes that will simultaneously make future tourism safer and make local residency more desirable and accessible. With those the host borough will be able to sustain impacts from Olympics and reap the most benefits from hosting the Games

Obtaining Net Effect of Olympics

Constructing Control Group

Local Trends

Obtain Non-London UK district data



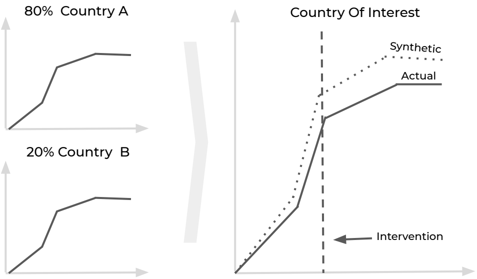
International Trends

Use KNN to obtain the most similar international city to London

Estimating True ATE of Olympics

Modified Synthetic Control

Using members of the Control Group, construct a synthetic control counterfactual for the GDP Per capita of London Boroughs and obtain net ATE for periods post Olympics



NPV of panel ATE

Using the Annuity formula and the corresponding interest rate, calculate the NPV of all net ATE in the future

Back Attribution to Borough Characteristic

ML based Attribution

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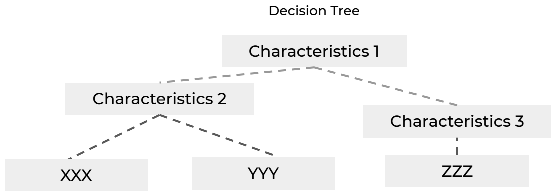

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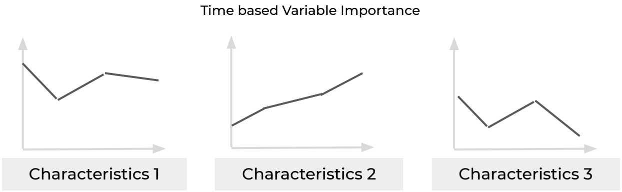

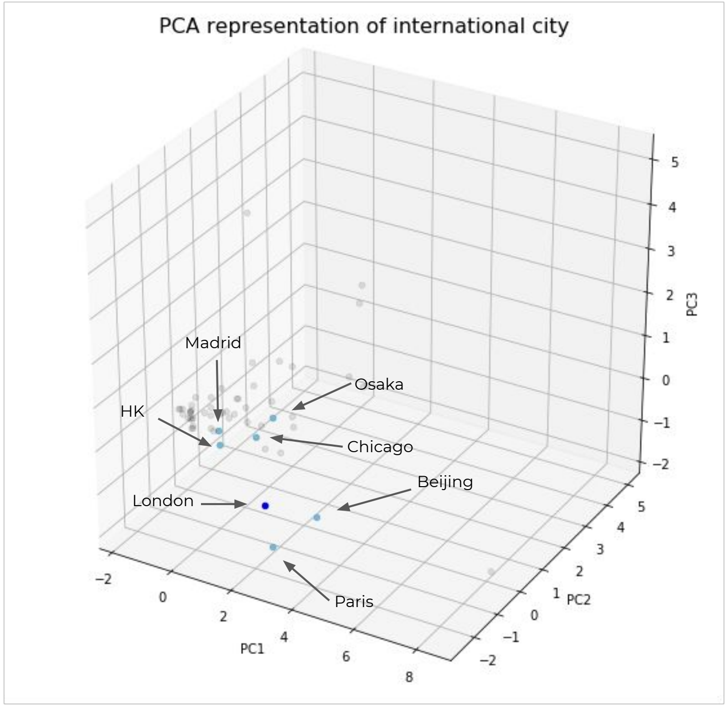
PCA representation of international city
Madrid
Osaka
HK
Chicago
London
Beijing
Paris
PC1
PC2
PC3

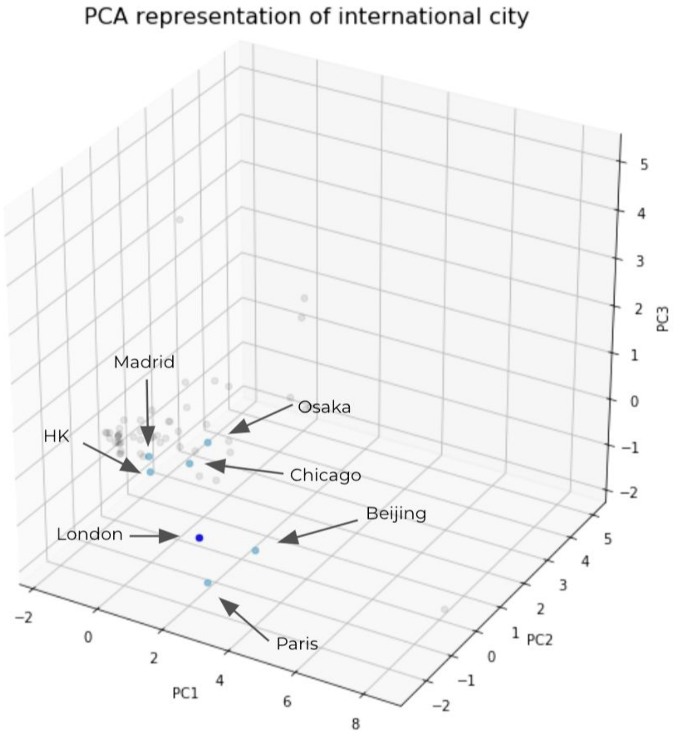
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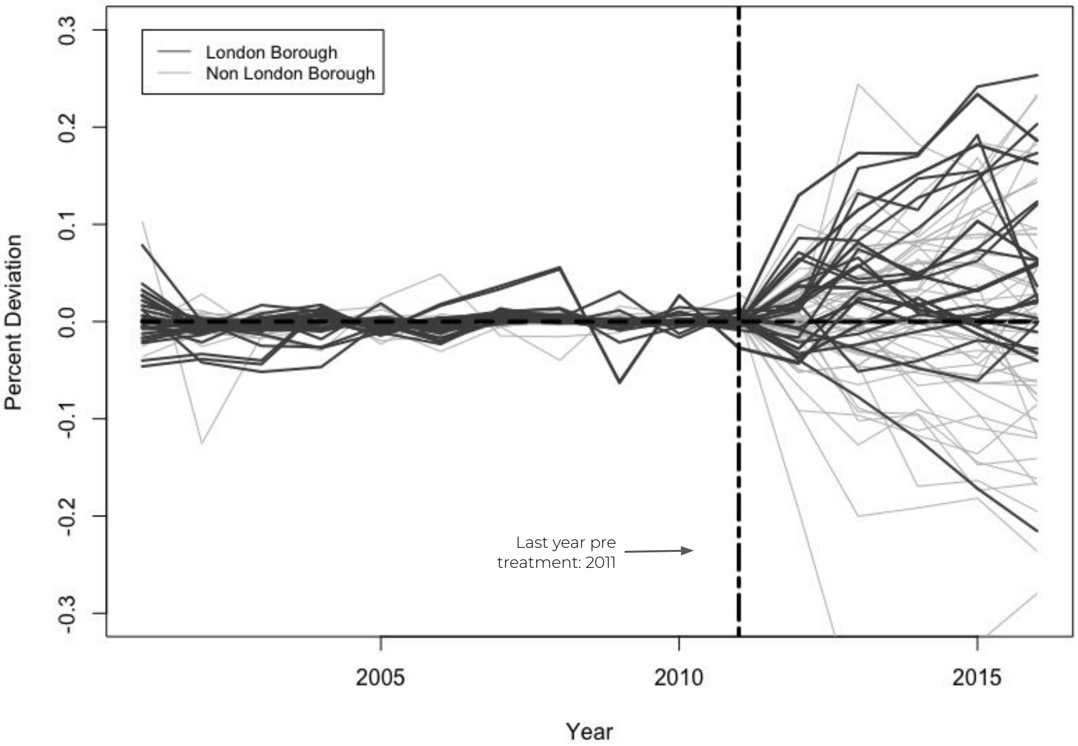
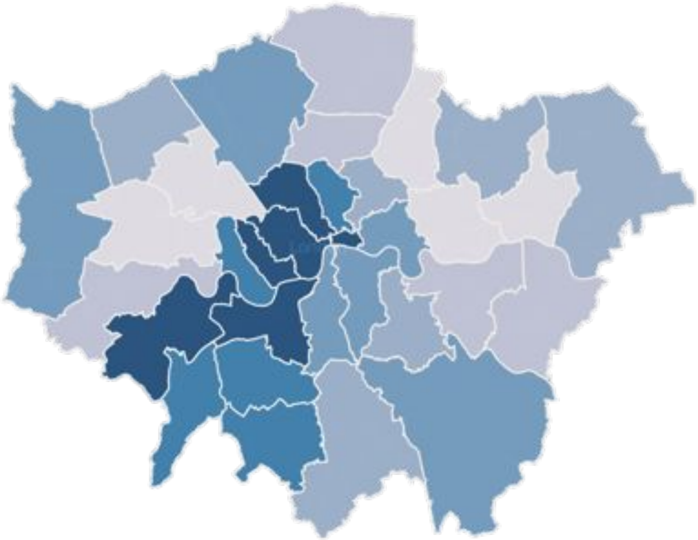
Table

	Year	Ith borough gdp	control borough 1 gdp	. . . .	control borough N gdp
Pre Treatment	2001	XXX	XXX		XXX
	....	....	....		....
Post Treatment	2012	YYY	YYY		YYY
	....	....	....		....
	2016	ZZZ	ZZZ		ZZZ
		Variable of Interest	Features		

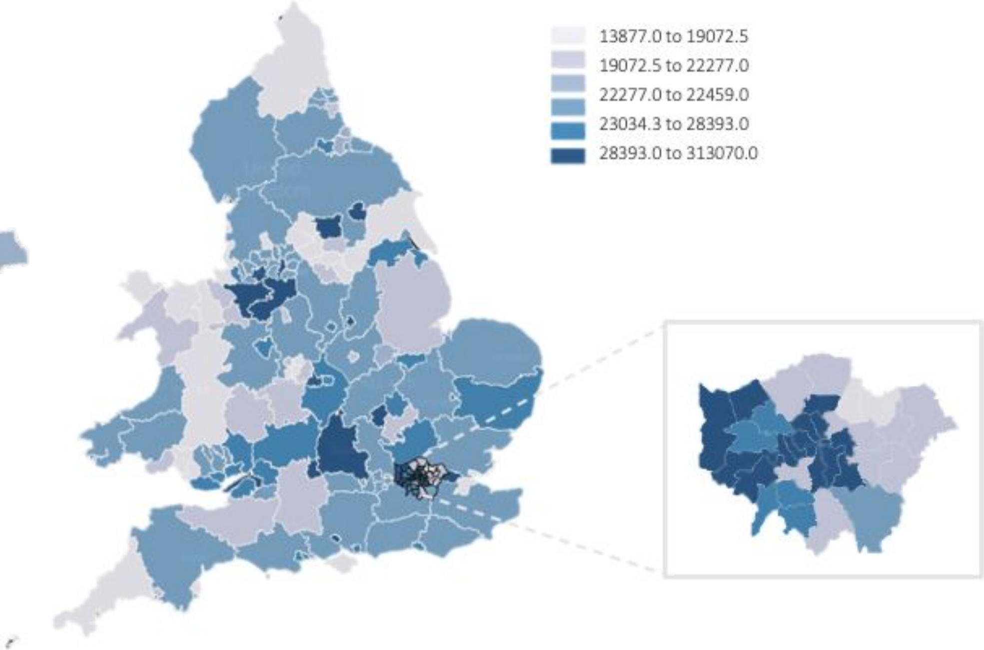
Margin difference between actual and synthetic control



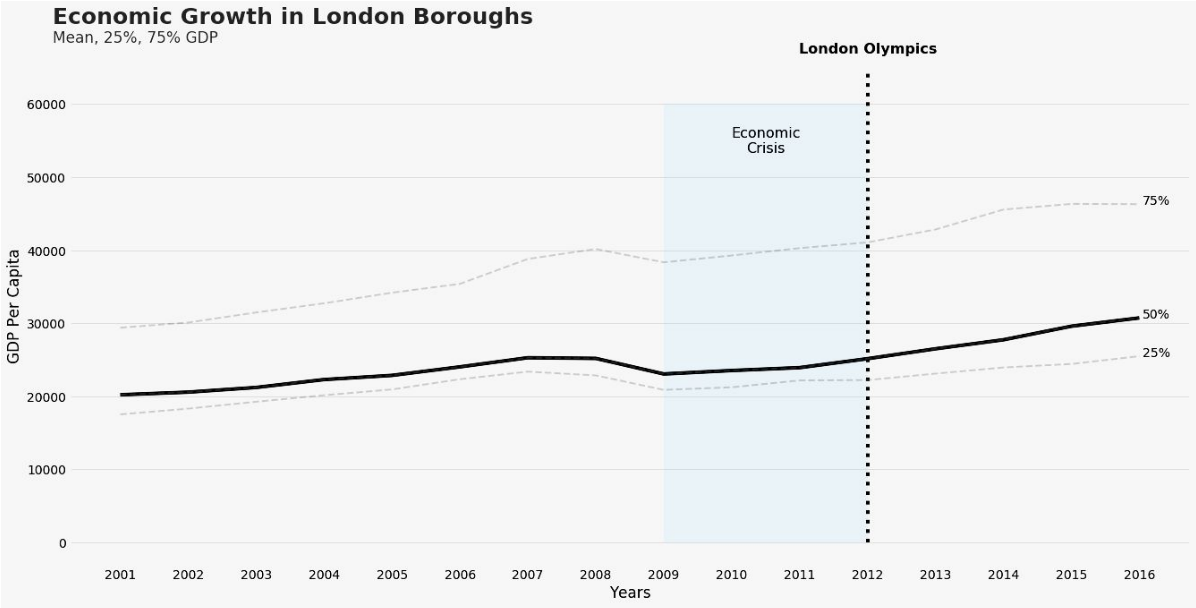
2011 London Taxpayer Median Income



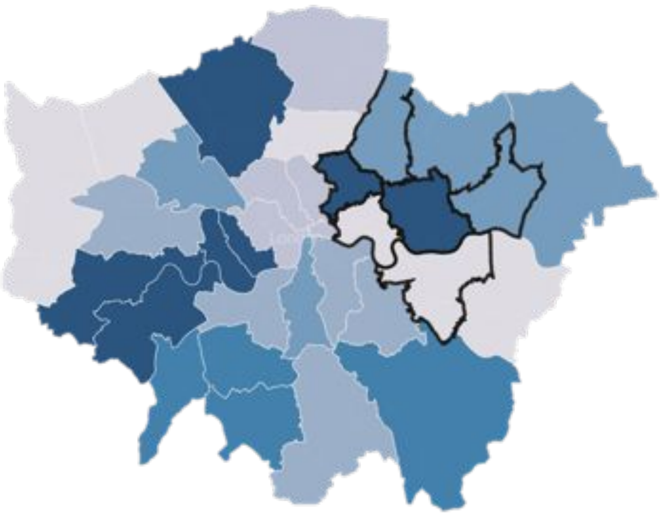
2011 UK GDP per capita (pounds)



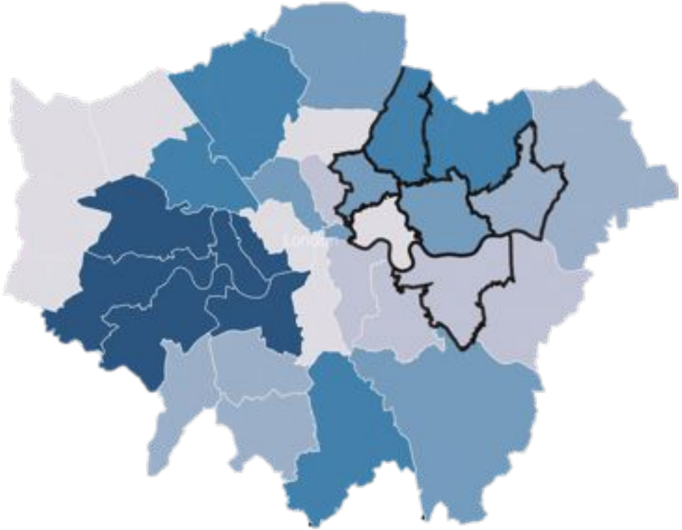
KEVIN IGNORED US :(

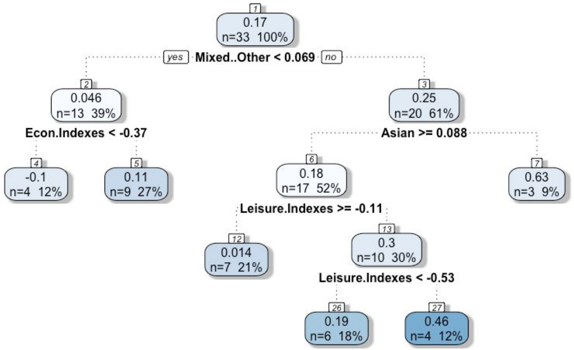


2012 GDP per capita margin **[Short Term]**



GDP NPV per capita margin (2012-2015) **[Long Term]**




1
0.17
n=33 100%
yes
Mixed..Other < 0.069
no
2
0.046
n=13 39%
Econ.Indexes < -0.37
3
0.25
n=20 61%
Asian >= 0.088
4
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6
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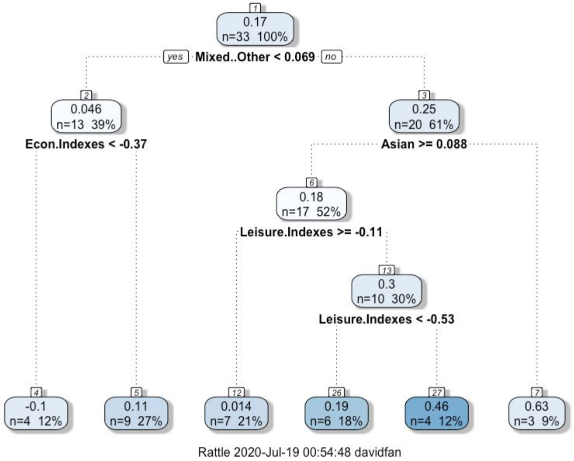
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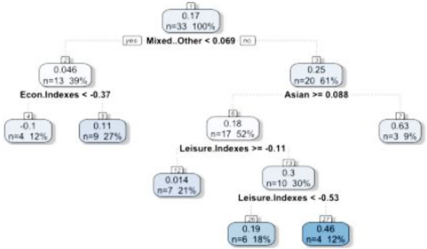
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