[Title]

Preparation

- Github link *[Optional]*

- Number of words: ***

- Runtime: *** hours (*Memory 10 GB, CPU Intel i7-10700 CPU @2.90GHz*)

- Coding environment: SDS Docker

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- Additional library *[libraries not included in SDS Docker or not used in this module]*:

    - **watermark**: A Jupyter Notebook extension for printing timestamps, version numbers, and hardware information.

    - To install required package:

```
!pip install linearmodels
!pip install nbconvert weasyprint
```

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Introduction

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Childhood obesity remains a critical public health challenge in London, adversely affecting children's health and causing significant economic costs. To address this, the UK government's *Childhood Obesity: A Plan for Action* (Department of Health and Social Care, 2018) substantially expanded investments in physical activity infrastructure, including funding for school sports and community facilities. Public Health England's *Local*

Health Profiles report increased availability of parks, playgrounds, and sports centres across London wards (Public Health England, 2023). Nonetheless, reductions in childhood obesity have been limited and uneven, especially among younger children, underscoring obesity's multifactorial nature and insufficient impact from infrastructure expansion alone (Wyszyńska et al., 2020; Lieb, 2009).

This study evaluates how different facility types influence childhood obesity rates across age groups in London wards between 2009/10 and 2013/14. Using NCMP data from 2008 to 2014, it also examines the moderating roles of socioeconomic status (SES), green space, and public transport accessibility. By leveraging spatial and temporal fixed effects, the research aims to uncover spatial heterogeneity and inform targeted, equitable public health strategies (Titis, 2023; Yuan, 2024).

Requirements to Run the Analysis

An overview of packages used to run the analysis with brief explanation of their role.

```
!pip install linearmodels
!pip install nbconvert weasyprint
```

```
import os
import requests
import zipfile
from functools import reduce

import pandas as pd
import geopandas as gpd
from shapely.geometry import Point

import numpy as np
import scipy.stats as stats

import matplotlib.pyplot as plt
from matplotlib.gridspec import GridSpec

import seaborn as sns

from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler

import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.iolib.summary2 import summary_col
from statsmodels.stats.outliers_influence import variance_inflation_factor

from linearmodels.panel import PanelOLS

import nbformat
import nbconvert
from nbconvert.exporters import HTMLExporter
from nbconvert.preprocessors import Preprocessor
from weasyprint import HTML, CSS
```

Literature Review

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Increasing evidence challenges the notion that expanding physical activity facilities alone suffices to reduce childhood obesity rates. While infrastructure is necessary, obesity results from complex interactions among behaviours, socioeconomic factors, and environmental contexts (Danielli et al., 2021). Research shows age influences intervention responses: older children engage more independently with their surroundings, whereas younger children's behaviours are more shaped by familial and cultural factors (Wyszyńska et al., 2020; Ayala et al., 2021), indicating the need for age-specific approaches.

Socioeconomic disparities exacerbate risk, as children from lower SES backgrounds often face poor access to quality facilities and supportive environments (Lieb et al., 2009; Yuan, 2024). Environmental factors such as green space and public transport accessibility further modify physical activity opportunities and obesity outcomes (Danielli et al., 2021). Additionally, spatial heterogeneity within London wards manifests uneven obesity prevalence and resources, warranting geographically targeted interventions (Titis et al., 2023).

This study's key innovation lies in integrating facility types, age, SES, and environmental factors within a spatial-temporal fixed effects framework. Unlike prior isolated or cross-sectional studies, this approach captures how facility effects vary across age and SES groups and reveals spatial differences in obesity patterns. Using fixed effects controls unobserved confounders across space and time, enabling more precise identification of heterogeneity. This comprehensive perspective supports the design of more targeted, equitable childhood obesity prevention policies.

Research questions

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Considering that facility types affect physical activity differently by children's developmental stages and mobility, and that socioeconomic disparities influence facility access and use, it is essential to study these factors separately. Environmental aspects like socioeconomic status, green space, and public transport accessibility (PTAL), integrated through spatial and temporal fixed effects, also shape activity opportunities and may modify these effects. Therefore, this study addresses the following:

RQ1: How do various facility types impact obesity rates among children of different age groups?

RQ2: To what extent do socioeconomic status, green space proportion, and public transport accessibility (PTAL) moderate the effects of facilities on childhood obesity, after controlling for spatial and temporal differences?

Recognizing that obesity prevalence and environmental influences vary across geographic areas and over time, a comprehensive spatial-temporal analysis is necessary. Consequently:

RQ3: How can spatial and temporal fixed effects reveal heterogeneous patterns to inform targeted public health interventions?

Data Collection

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This study focuses on London wards at the 2011 level (London Data Store, 2011), offering the finest publicly available spatial resolution. The research covers the academic years from 2010/2011 to 2013/2014, spanning four academic years in total.

Table 3.1: Variable Descriptions and Data Sources for Urban Childhood Obesity Analysis

Variable Category	Variable Name	Description	Time Coverage	Data Source
Obesity Rates	`obese_recp`	Reception children obesity (ages 4-5)	2010/2011–2013/2014	Ward Atlas-NCMP
	`obese_y6`	Year 6 children obesity (ages 10-11)	2010/2011–2013/2014	Ward Atlas-NCMP
Facility Types	`facility_edu`	Education facilities per 10,000 pop	2010–2014	Active Places, ONS
	`facility_comm`	Commercial facilities per 10,000 pop	2010–2014	Active Places, ONS
	`fac_density_local`	Local authority facilities per 10,000 pop	2010–2014	Active Places, ONS
Socioeconomic	`unemployment_rate`	Unemployment rate	2010–2014	Ward Profiles
Environmental	`greenspace_pct`	Percentage of greenspace	2010, 2012*	Ward Profiles
	`ptal`	Public Transport Accessibility Level	2010, 2011, 2012, 2014*	Ward Profiles

[Note: Missing years for greenspace and PTAL were estimated via interpolation as described below.]

1. Facilities were filtered to include only those operational before 2014 by considering their opening and closing dates. Population estimates for wards each year were taken from the Office for National Statistics (ONS, 2023). Facility density per 10,000 population was calculated using the formula:

$$ \text{Facility density} = \frac{\text{Number of operational facilities in ward}}{\text{Ward population}} \times 10,000 $$

This calculation standardises facility counts by population size, enabling meaningful comparison across wards with differing population numbers.

1. Linear interpolation was applied to address missing years in greenspace and PTAL data. The method assumes that changes between two observed values occur in a steady, linear fashion over time and estimates missing values accordingly by proportionate weighting between neighbouring data points.

This approach is reliable because environmental variables like greenspace and PTAL typically evolve gradually over short periods, and the brief interpolation spans (one to two years) minimise potential inaccuracies. Linear interpolation is a well-established technique in spatial-temporal data analysis, supported by comprehensive reviews such as Li et al., 2014.

After cleaning and interpolation, all datasets were merged on the standard geographic identifier (ward_code) to produce a comprehensive dataset for analysis.

Methodology

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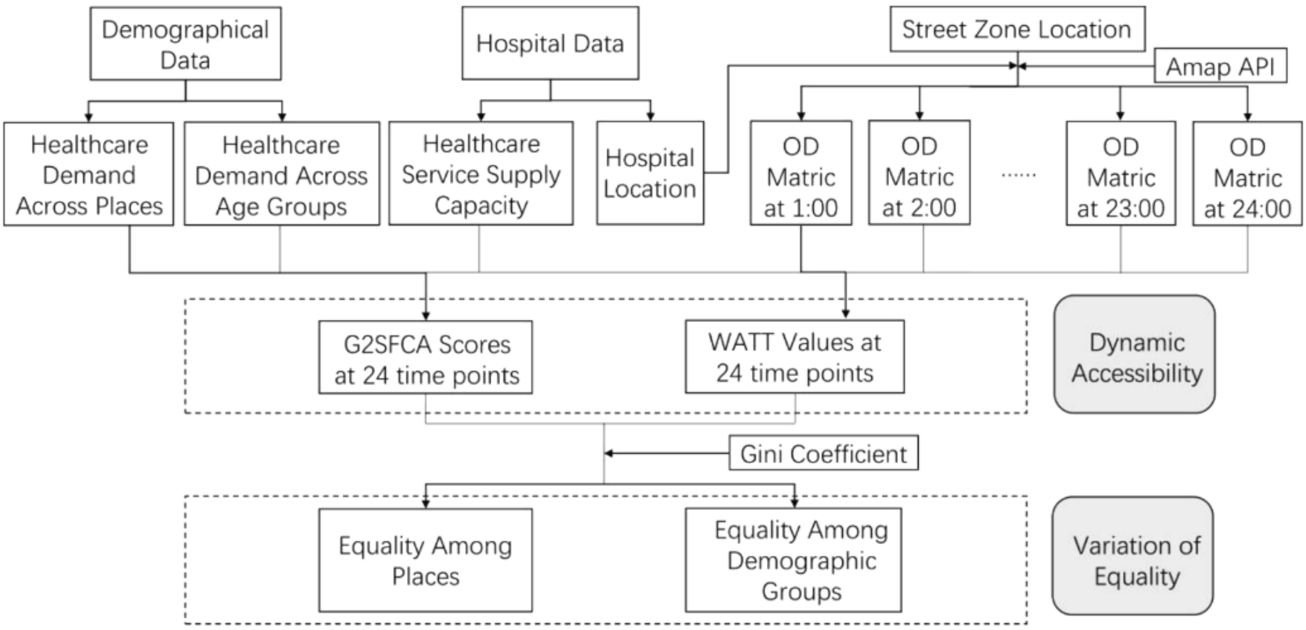
[Note: a flow chart that describes the methodology is strongly encouraged - see the example below. This flow chart can be made using Microsoft powerpoint or visio or other software]

Source: see link.



Results and discussion

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Conclusion

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References

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