[Title]

Preparation

- Github link *[Optional]*
- Number of words: ***
- Runtime: *** hours (*Memory 10 GB, CPU Intel i7-10700 CPU @2.90GHz*)
- Coding environment: SDS Docker
- License: this notebook is made available under the Creative Commons Attribution license (or other license that you like).
- 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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1. 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 aims to quantitatively evaluate how different facility types influence childhood obesity rates across age groups in London wards from 2009/10 to 2013/14. It also examines the moderating roles of socioeconomic status (SES), green space, and public transport accessibility (PTAL). Leveraging spatial and temporal fixed effects, this research seeks to uncover spatial heterogeneity and construct a novel risk-intervention two-dimensional quadrant framework combining spatial fixed effects and residuals to guide targeted, equitable public health interventions.

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
```

```

```

2. 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).

Notably, Nau et al. (2019) used panel data integrating socioeconomic and built environment factors to study youth BMI trajectories across diverse communities, emphasizing the importance of accounting for spatial and temporal heterogeneity and dynamic interactions over time in obesity research.

Building on these foundations, the present study integrates facility types, age groups, SES, and environmental factors within a spatial-temporal fixed effects framework. This approach aims to better capture how facility impacts vary by age and SES while precisely modeling spatial heterogeneity in childhood obesity patterns, thereby informing more nuanced, targeted interventions.

3. Research questions

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Building on the above, and given that facility effects vary by children’s development and socioeconomic access, while environmental factors (SES, greenspace, PTAL) may modify these effects through space and time, this study addresses:

- **RQ1 |** How do different facility types affect childhood obesity across age and socioeconomic groups, after accounting for spatial and temporal factors?
- **RQ2 |** How do greenspace and public transport accessibility modify the effects of facilities on obesity?

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?

4. 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
	`facility_local`	Local authority facilities per 10,000 pop	2010–2014	Active Places, ONS
Socioeconomic	`unemp`	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.]

The key independent variables are densities of physical activity facilities, with the proportion of children from unemployed households and children's age groups used as heterogeneity stratifiers; greenspace coverage and public transport accessibility (PTAL) are included as control variables.

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:

$$\textbf{Facility density} = \textbf{(Number of operational facilities in ward / Ward population)} \times \textbf{10,000}$$

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

```
# Count active facilities per ward per year
def count_facilities_by_ward(gdf_fac_london, years, facility_types):
    wards_fac_count = wards[ward_cols].copy()
    for yr in years:
        # Filter active facilities for the year
        mask_active = (
            (gdf_fac_london['year_built'] <= yr) &
            (gdf_fac_london['closed_date'].isna() |
```

```python
(gdf_fac_london['closed_date'].dt.year >= yr))
        )
        active = gdf_fac_london[mask_active]

        # Count facilities by type for each ward
        for ftype in facility_types:
            temp = active[active['mgmt_group'] == ftype]
            by_ward = temp.groupby('GSS_CODE').size().rename(f'facility_{ftype.lower()}
_{yr}').reset_index()
            wards_fac_count = wards_fac_count.merge(by_ward, on='GSS_CODE', how='left')

    # Fill missing values with 0
    for ftype in facility_types:
        for yr in years:
            col = f'facility_{ftype.lower()}_{yr}'
            if col in wards_fac_count.columns:
                wards_fac_count[col] = wards_fac_count[col].fillna(0)

    return wards_fac_count
```

```python

```

```python
# Compute facility density per 10,000 population
def compute_facility_density(wards_fac_count, df_pop, pop_years, facility_types,
ward_cols):
    wards_fac_pop = wards_fac_count.merge(df_pop, on='GSS_CODE', how='left')

    for yr in pop_years:
        for ftype in facility_types:
            fac_col = f'facility_{ftype.lower()}_{yr}'
            wards_fac_pop[f'facility_{ftype.lower()}_per_10000pop_{yr}'] = (
                wards_fac_pop[fac_col] / wards_fac_pop[f'pop_{yr}'] * 10000
            )

    to_keep = ward_cols.copy()
    for yr in pop_years:
        for ftype in facility_types:
            to_keep.append(f'facility_{ftype.lower()}_per_10000pop_{yr}')

    return wards_fac_pop[to_keep]

# Main execution
wards_fac_count = count_facilities_by_ward(gdf_fac_london, years, facility_types)
df_pop = load_population_data(pop_years)
wards_fac_pop = compute_facility_density(wards_fac_count, df_pop, pop_years,
facility_types, ward_cols)
```

```python

```

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.

```
# Interpolate missing years
df_green["greenspace_pct_2011"] = df_green["greenspace_pct_2012"]
df_green["greenspace_pct_2013"] = (df_green["greenspace_pct_2012"] +
df_green["greenspace_pct_2014"]) / 2
df_ptal["ptal_2013"] = (df_ptal["ptal_2012"] + df_ptal["ptal_2014"]) / 2
```

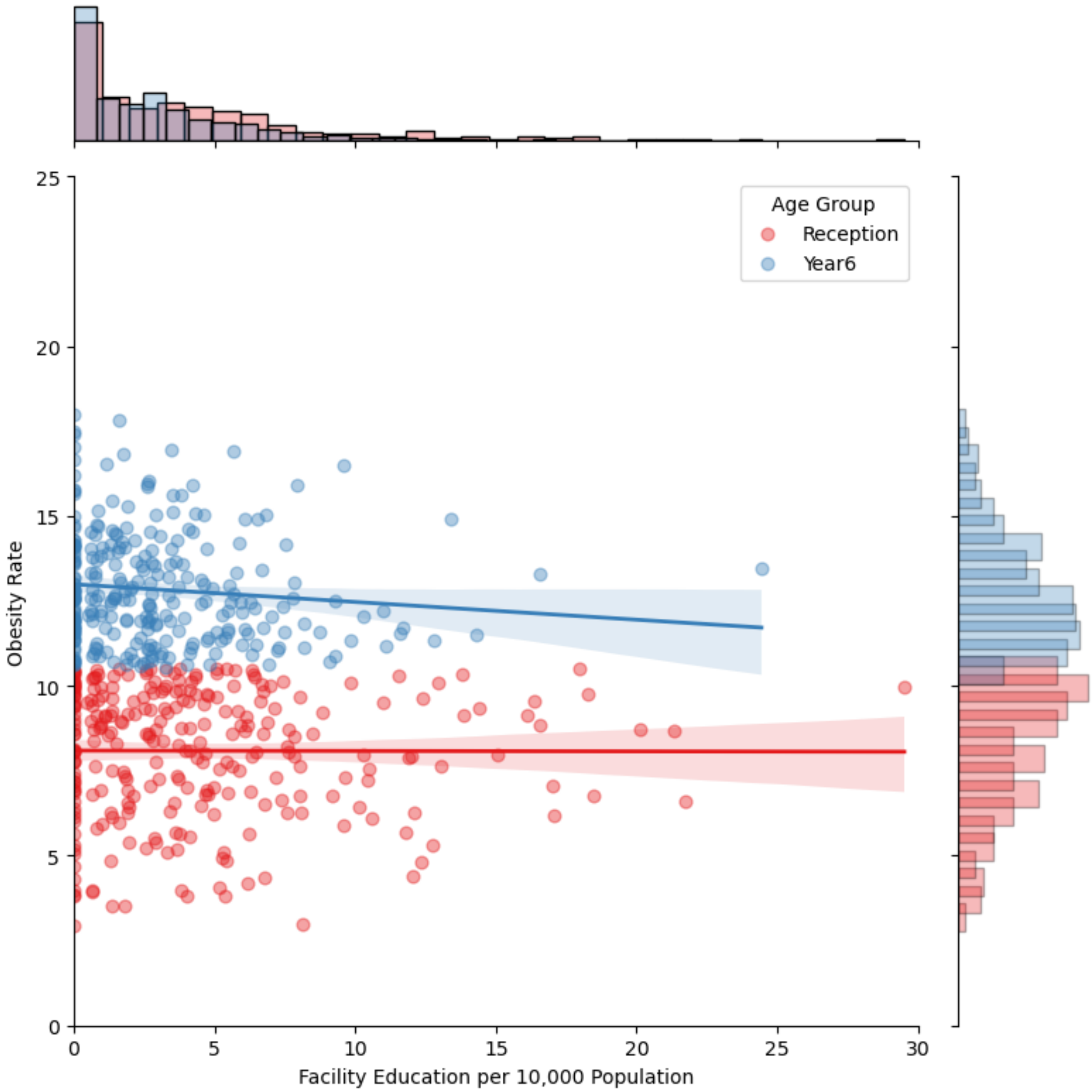
After cleaning and interpolation, all datasets were merged on the standard geographic identifier (ward_code) to produce a comprehensive dataset for analysis.

```

```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 654 entries, 0 to 653
Data columns (total 38 columns):
 #   Column                                    Non-Null Count  Dtype
---  ------                                    --------------  -----
 0   NAME                                      654 non-null    object
 1   GSS_CODE                                  654 non-null    object
 2   BOROUGH                                   654 non-null    object
 3   geometry                                  654 non-null    geometry
 4   facility_education_per_10000pop_2011      570 non-null    float64
 5   facility_education_per_10000pop_2012      637 non-null    float64
 6   facility_education_per_10000pop_2013      637 non-null    float64
 7   facility_education_per_10000pop_2014      637 non-null    float64
 8   facility_commercial_per_10000pop_2011     570 non-null    float64
 9   facility_commercial_per_10000pop_2012     637 non-null    float64
 10  facility_commercial_per_10000pop_2013     637 non-null    float64
 11  facility_commercial_per_10000pop_2014     637 non-null    float64
 12  facility_local authority_per_10000pop_2011  570 non-null    float64
 13  facility_local authority_per_10000pop_2012  637 non-null    float64
 14  facility_local authority_per_10000pop_2013  637 non-null    float64
 15  facility_local authority_per_10000pop_2014  637 non-null    float64
 16  obese_recp_2008_2011                      559 non-null    float64
 17  obese_recp_2009_2012                      559 non-null    float64
 18  obese_recp_2010_2013                      561 non-null    float64
 19  obese_recp_2011_2014                      561 non-null    float64
 20  obese_y6_2008_2011                        567 non-null    float64
 21  obese_y6_2009_2012                        567 non-null    float64
 22  obese_y6_2010_2013                        567 non-null    float64
 23  obese_y6_2011_2014                        561 non-null    float64
 24  unemp_2010                                570 non-null    float64
 25  unemp_2011                                570 non-null    float64
 26  unemp_2012                                570 non-null    float64
 27  unemp_2013                                570 non-null    float64
 28  unemp_2014                                570 non-null    float64
 29  greenspace_pct_2011                       570 non-null    float64
 30  greenspace_pct_2012                       570 non-null    float64
 31  greenspace_pct_2013                       570 non-null    float64
 32  greenspace_pct_2014                       570 non-null    float64
 33  ptal_2010                                 570 non-null    float64
 34  ptal_2011                                 570 non-null    float64
 35  ptal_2012                                 570 non-null    float64
 36  ptal_2013                                 570 non-null    float64
 37  ptal_2014                                 570 non-null    float64
dtypes: float64(34), geometry(1), object(3)
memory usage: 194.3+ KB
None
```

:



5. Methodology

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Following Nau et al. (2019), this study analyses childhood obesity across London wards from 2010 to 2014 using panel data integrating socioeconomic and built environment variables. We develop age-specific fixed effects regression models at a fine ward-level scale, incorporating detailed facility types, age groups (Reception and Year 6), and their interactions with socioeconomic status (SES). This framework enables comprehensive control over spatial and temporal heterogeneity, while also accounting for residual variation and inherent spatial risk (see Figure 2).

5.1 Multicollinearity Testing

Multicollinearity is first assessed using Variance Inflation Factor (VIF) and Pearson correlation matrix to avoid high correlations among independent variables that may bias model estimation (Hair et al., 2019):

- Variables with VIF > 5 are removed or transformed to ensure predictor independence.
- Variables with absolute Pearson correlation coefficients > 0.7 are excluded.

This procedure ensures stability and interpretability of subsequent panel regression models.

5.2 Cross-sectional OLS Regression

We conduct annual cross-sectional Ordinary Least Squares (OLS) regressions—a standard method estimating linear relationships—to assess baseline spatial associations between childhood obesity and variables. Treating years independently captures spatial variation but omits time-invariant unobserved factors.

This approach provides important guidance on variable selection and model set-up for panel fixed effects models that address temporal dynamics and unobserved heterogeneity.

5.3 Panel Fixed Effects Regression Model

Based on the screened facility and socioeconomic variables, a panel fixed effects regression model is constructed using ward-level data from 2010 to 2014 to analyse spatial and temporal variations of childhood obesity rates. The fixed effects model effectively controls for time-invariant regional characteristics and annual uniform impacts, reducing omitted variable bias and improving causal inference robustness.

The baseline model is expressed as follows:

$$\mathbf{Obesity_{i,t} = \alpha + \sum_k \beta_k\, Facility_{k,i,t} + \gamma_1\, Unemployment_{i,t} + \gamma_2\, Greenspace_{i,t} + \gamma_3\, PTAL_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t}}$$

where:

- $\mathrm{Obesity}_{i,t}$: Childhood obesity rate of ward i in year t
- $\mathrm{Facility}_{k,i,t}$: Density of facility type k in ward i and year t
- $\mathrm{Unemp}_{i,t}$, $\mathrm{Greenspace}_{i,t}$, $\mathrm{PTAL}_{i,t}$: Control variables for unemployment rate, greenspace coverage, and public transport accessibility level respectively
- μ_i: Ward fixed effects controlling for time-invariant regional characteristics
- τ_t: Year fixed effects controlling for common annual shocks
- $\varepsilon_{i,t}$: Error term

Models are estimated separately for Reception (ages 4-5) and Year 6 (ages 10-11) groups to examine heterogeneous effects across developmental stages.

Further, interaction terms between facility variables and socioeconomic status (SES) are incorporated:

$$\text{Obesity}_{i,t} = \alpha + \Sigma_k \beta_k \text{Facility}_{k,i,t} + \Sigma_k \delta_k (\text{Facility}_{k,i,t} \times \text{SES}_{i,t}) + \gamma_1 \text{Unemployment}_{i,t} + \gamma_2 \text{Greenspace}_{i,t} + \gamma_3 \text{PTAL}_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t}$$

which explores how SES moderates the impact of different facility types on childhood obesity, enhancing the policy relevance and scientific rigour of recommendations.

5.4 Residuals and Spatial Heterogeneity Analysis

Inspired by approaches combining spatial risk assessment with local variation analysis (Walker et al., 2016), we leverage spatial fixed effects and residuals to capture inherent spatial risk across wards and unexplained local deviations under current government interventions. To apply this insight, we construct a two-dimensional quadrant plot classifying wards by spatial risk level and residual sign.

This classification identifies:

- **High spatial risk & positive residuals**: Persistent high-risk wards where obesity remains above expected levels, suggesting current interventions are insufficient.
- **High spatial risk & negative residuals**: Wards with high inherent risk but better-than-expected outcomes, indicating effective local measures.
- **Low spatial risk & positive residuals**: Wards usually at low risk but showing unexpected obesity increases, signalling emerging problems.
- **Low spatial risk & negative residuals**: Wards with low risk and favourable outcomes, representing stable, well-managed areas.

By combining spatial risk and residual deviations, this approach highlights where current strategies succeed or fail, guiding more precise resource allocation and multi-level public health actions.

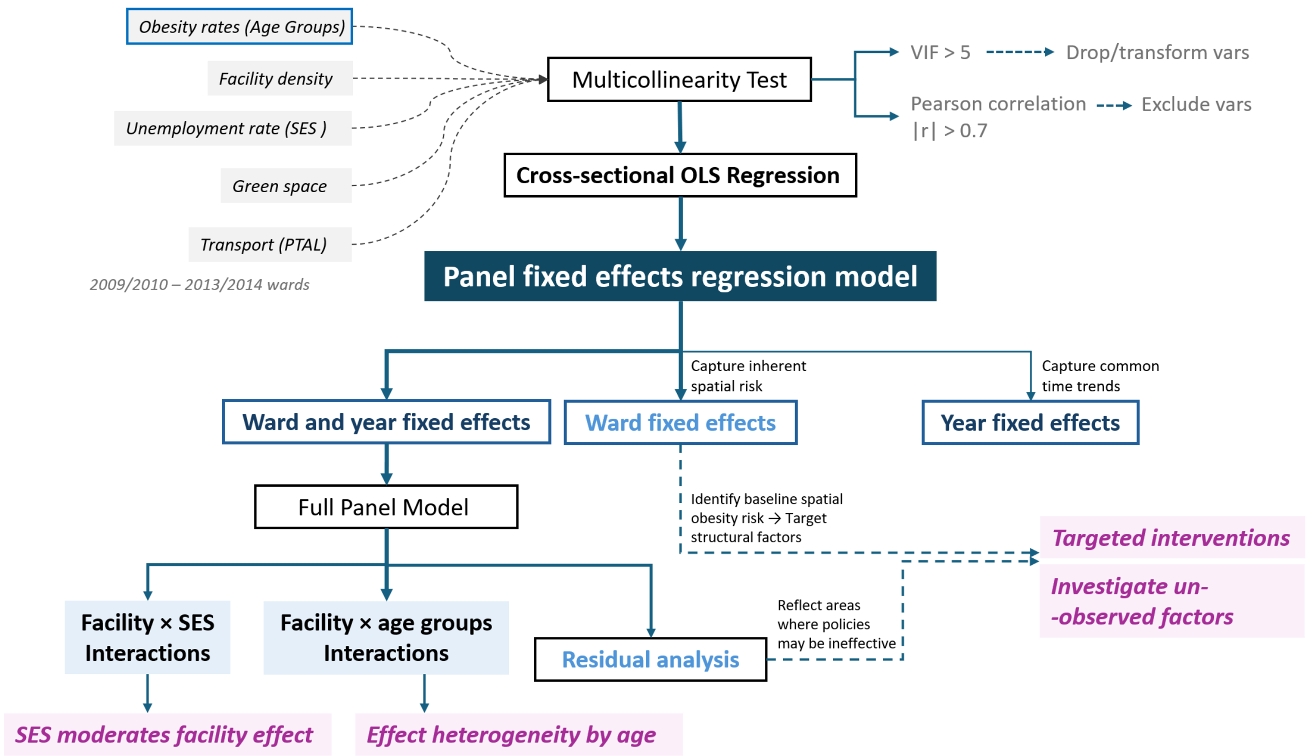

Figure 2: Methodology flow chart.

6. Results Analysis

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6.1 Multicollinearity Check and Panel data Preparetion

Table 2 and Figure 3 indicate all explanatory variables have acceptable multicollinearity (VIF < 5). Facility variables show moderate correlations (up to 0.35), while socioeconomic and environmental variables display expected patterns, justifying their inclusion in regression models.

Table 2. Variance Inflation Factor (VIF) for Explanatory Variables

```
# Define features for VIF and correlation
features = ['facility_education', 'facility_commercial', 'facility_local_authority',
'unemployment', 'greenspace', 'ptal']

# Calculate VIF for multicollinearity check
X = data_clean[features].values
vif_data = pd.DataFrame({'Variable': features, 'VIF': [variance_inflation_factor(X, i)
for i in range(X.shape[1])]})
print(vif_data)

# Compute and plot correlation matrix including obesity
corr_matrix = data_clean[features + ['obesity']].corr()
```

	Variable	VIF
0	facility_education	2.037713
1	facility_commercial	1.573460
2	facility_local_authority	1.449113
3	unemployment	3.592629
4	greenspace	3.324651
5	ptal	4.200670

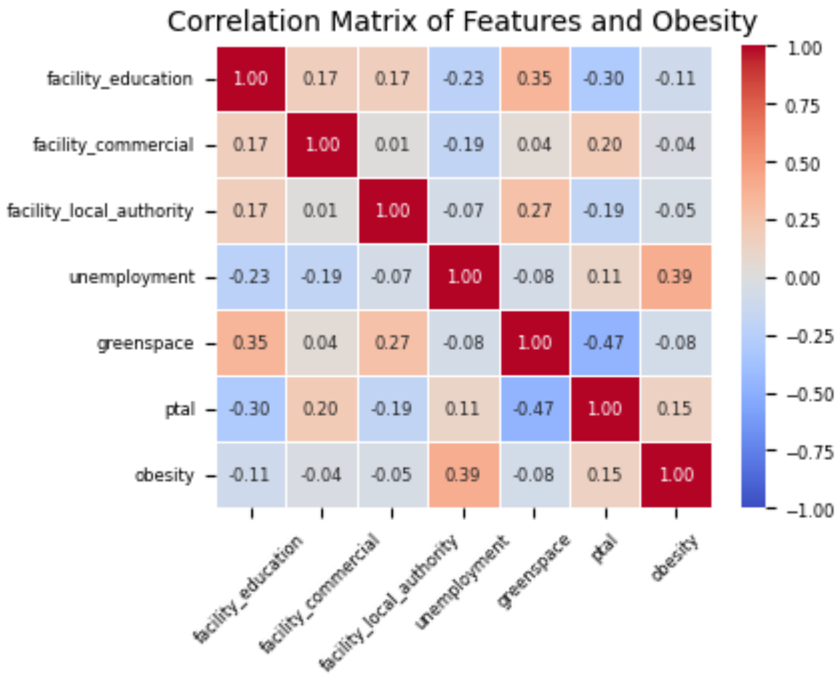


Figure 3. Correlation Matrix of Features and Obesity

```
 
```

Next, the dataset were reorganised into long format by concatenation and set with ward and year as panel indices for regression analysis.

```
# Concatenate data for all years
panel_df = pd.concat(panel_list, axis=0).reset_index(drop=True)

# Set panel index for panel regression (ward_code and year)
panel_df = panel_df.set_index(['ward_code', 'year'])
```

5.2 Cross-Sectional OLS Regression Results

Table 3 presents cross-sectional OLS results for 2011–2014. Facility variables exhibit heterogeneity, with coefficients fluctuating between significant and nonsignificant across years; education-related facilities are borderline significant (~0.04). Public transport accessibility (ptal) consistently shows a positive and highly significant association with childhood obesity. Unemployment positively, and greenspace negatively, affect obesity rates significantly.

Figure 4 highlights varied ward-level slopes between facility_education and Year 6 obesity, confirming heterogeneous facility effects.

Table 3. Cross-Sectional OLS Regression Results (2011–2014)

```
panel_df_reset = panel_df.reset_index()
models = []
model_names = []
```

```python
for year in sorted(panel_df_reset['year'].unique()):
    sub = panel_df_reset[panel_df_reset['year'] == year]
    model = smf.ols("obesity_year6 ~ facility_education + facility_commercial +
facility_local_authority + unemployment + greenspace_pct + ptal", data=sub).fit()
    models.append(model)
    model_names.append(str(year))

table = summary_col(models, stars=True, model_names=model_names,
                    info_dict={"N": lambda x: f"{int(x.nobs)}"},
                    float_format="%.3f")
print(table)
```

```
=================================================================
                           2011      2012      2013      2014
-----------------------------------------------------------------
Intercept                12.759*** 13.216*** 13.480*** 14.293***
                         (0.729)   (0.754)   (0.723)   (0.739)
facility_education       0.020     0.031     0.034     0.022
                         (0.040)   (0.042)   (0.041)   (0.043)
facility_commercial      0.046     0.054     0.058     0.034
                         (0.045)   (0.046)   (0.044)   (0.046)
facility_local_authority -0.056    -0.060    0.034     0.007
                         (0.109)   (0.111)   (0.108)   (0.113)
unemployment             0.007***  0.008***  0.009***  0.011***
                         (0.000)   (0.000)   (0.000)   (0.001)
greenspace_pct           -0.006    -0.013    -0.010    -0.027**
                         (0.010)   (0.010)   (0.010)   (0.011)
ptal                     0.830***  0.770***  0.601***  0.546***
                         (0.142)   (0.146)   (0.138)   (0.142)
R-squared                0.481     0.487     0.508     0.506
R-squared Adj.           0.475     0.481     0.503     0.501
N                        567       567       567       561
=================================================================
Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01
```

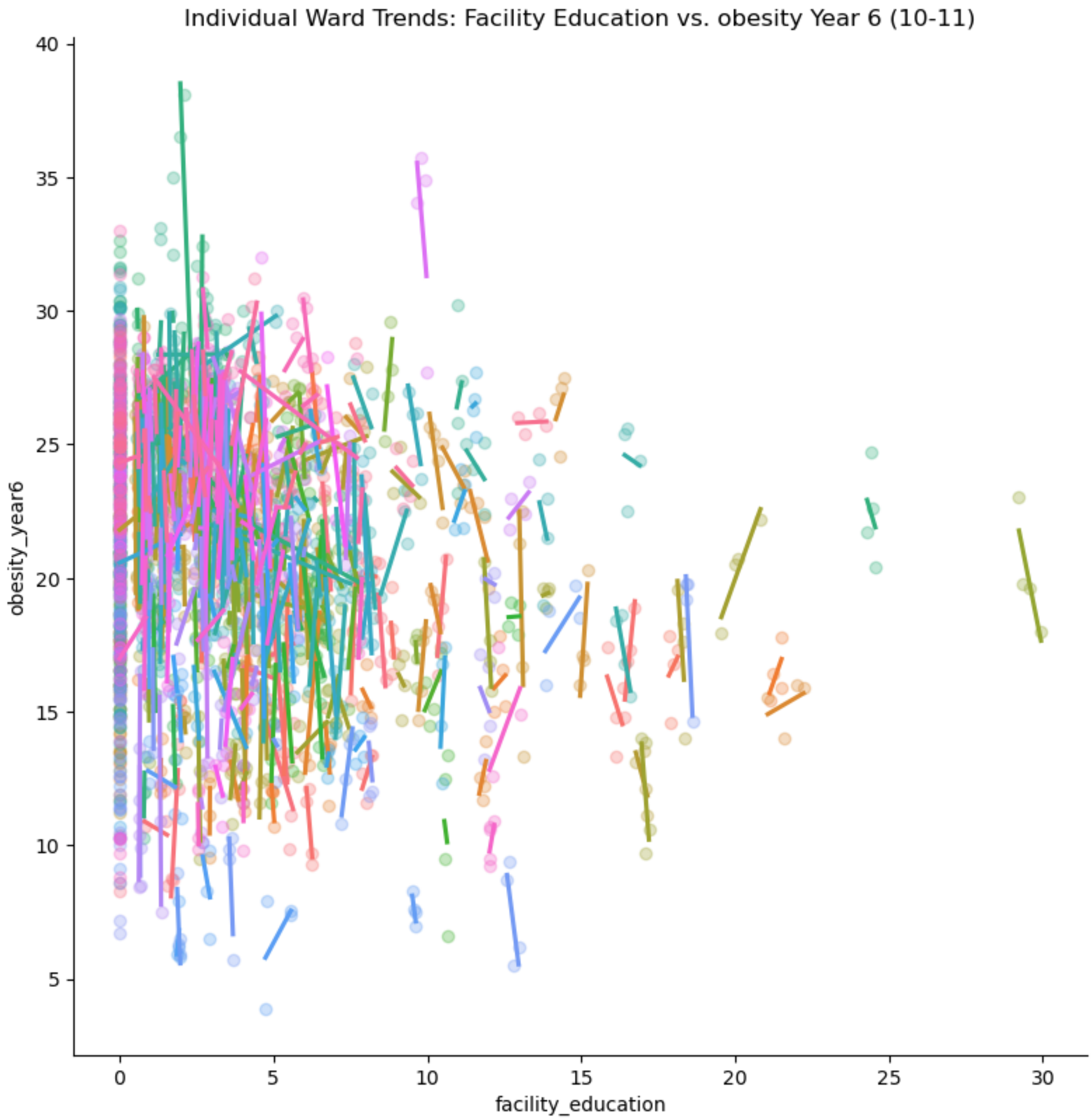


Figure 4. Ward-Level Slopes of Facility Education vs. Year 6 (10-11) Obesity

5.3 Panel Regression Results

The fixed effects panel model (Table 4) shows local authority facilities (facility_local_authority) significantly increase childhood obesity rates ($p = 0.0215$), while other facility types are not significant. This positive association may reflect reverse causality, with higher obesity areas receiving more local authority investments (see code below).

Unemployment shows a negative but insignificant association ($p = 0.123$). Greenspace coverage (greenspace_pct) consistently exhibits a significant protective effect ($p = 0.013$). The model's F-test (12.956, $p < 0.001$) supports the panel approach.

Time fixed effects reveal a gradual increase in obesity rates from 2011 to 2014.

Table 4. Panel Regression Results (Fixed Effects Model)

```python
panel_data = panel_df_reset.set_index(['ward_code', 'year'])

# Prepare dependent and independent variables
y = panel_data['obesity_year6']
X = panel_data[['facility_education', 'facility_commercial', 'facility_local_authority',
                'unemployment', 'greenspace_pct', 'ptal']]
X = sm.add_constant(X)  # Add intercept term

# Specify and fit the fixed effects panel model with entity and time effects
model_fe = PanelOLS(y, X, entity_effects=True, time_effects=True)
result_fe = model_fe.fit(cov_type='clustered', cluster_entity=True)

# Output model summary results
print(result_fe)
```

```
                          PanelOLS Estimation Summary
================================================================================
Dep. Variable:          obesity_year6   R-squared:                        0.0074
Estimator:                   PanelOLS   R-squared (Between):             -0.2555
No. Observations:                2262   R-squared (Within):               0.0194
Date:                Tue, Apr 29 2025   R-squared (Overall):             -0.2269
Time:                        08:38:35   Log-likelihood                   -4276.2
Cov. Estimator:             Clustered
                                        F-statistic:                      2.1064
Entities:                         567   P-value                           0.0497
Avg Obs:                       3.9894   Distribution:                  F(6,1686)
Min Obs:                       3.0000
Max Obs:                       4.0000   F-statistic (robust):             2.7466
                                        P-value                           0.0117
Time periods:                       4   Distribution:                  F(6,1686)
Avg Obs:                       565.50
Min Obs:                       561.00
Max Obs:                       567.00

                                   Parameter Estimates
============================================================================================
                          Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
--------------------------------------------------------------------------------------------
const                        25.620     3.4231     7.4845     0.0000      18.906      32.334
facility_education          -0.2060     0.2595    -0.7938     0.4274     -0.7149      0.3029
facility_commercial          0.1139     0.4124     0.2763     0.7824     -0.6949      0.9228
facility_local_authority     0.8620     0.3747     2.3004     0.0215      0.1270      1.5969
unemployment                -0.0015     0.0010    -1.5421     0.1232     -0.0033      0.0004
greenspace_pct              -0.1010     0.0406    -2.4875     0.0130     -0.1806     -0.0214
ptal                        -0.2622     0.8717    -0.3008     0.7636     -1.9718      1.4474
============================================================================================

F-test for Poolability: 12.956
P-value: 0.0000
Distribution: F(569,1686)

Included effects: Entity, Time
```

```
<Figure size 1000x600 with 0 Axes>
```

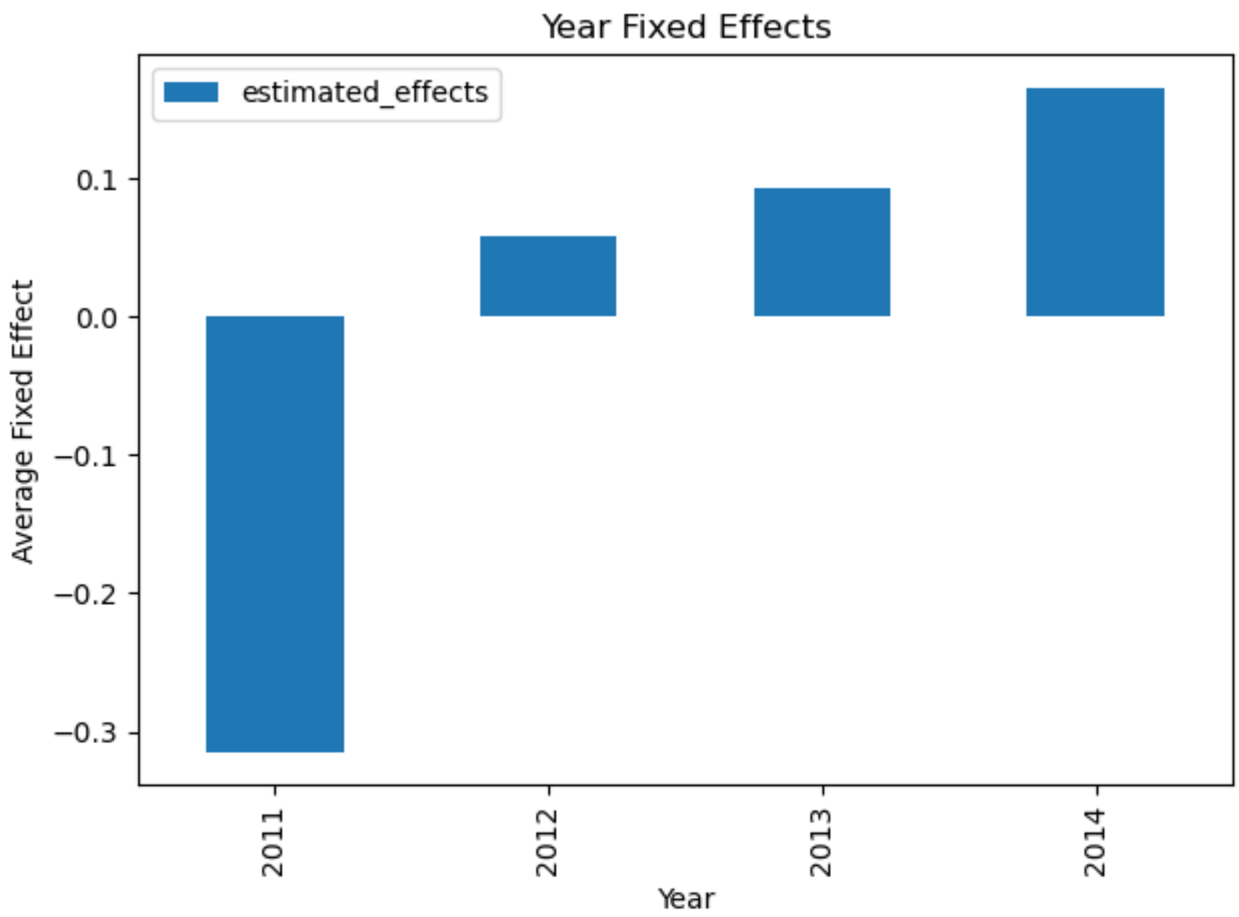


Figure 5. Year Fixed Effects of Obesity

5.4 Age-Group Panel Models

Sample stratification into Reception (4–5 years) and Year 6 (10–11 years) groups (Table 5) shows:

- No facility or socioeconomic variables are significant in Reception.
- In Year 6, facility_local_authority retains a significant positive effect ($p = 0.0215$), and greenspace coverage remains a significant negative influence ($p = 0.013$). Unemployment remains insignificant.

Older children's obesity rates appear more sensitive to environmental facilities and socioeconomic factors.

Table 5. Panel Model Results by Age Group (Reception and Year 6 Combined)

```
# Define outcome variables by age group
age_groups = {
    'Reception': 'obesity_reception',  # 4-5 years old
    'Year6': 'obesity_year6'           # 10-11 years old
}

results_by_age = {}

for group, outcome in age_groups.items():
    # Subset data and drop missing values
    data_sub = panel_data.dropna(subset=[outcome, 'facility_education',
```

```
'facility_commercial',
                                        'facility_local_authority', 'unemployment',
'greenspace_pct', 'ptal'])
    y = data_sub[outcome]
    X = sm.add_constant(data_sub[['facility_education', 'facility_commercial',
'facility_local_authority',
                                 'unemployment', 'greenspace_pct', 'ptal']])

    # Fit fixed effects panel model
    model = PanelOLS(y, X, entity_effects=True, time_effects=True)
    result = model.fit(cov_type='clustered', cluster_entity=True)
    results_by_age[group] = result

    print(f"\n===== Panel Results for {group} group =====")
    print(result.summary.tables[1])
```

```
===== Panel Results for Reception group =====
                                    Parameter Estimates
============================================================================================
                          Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
--------------------------------------------------------------------------------------------
const                        14.242     2.0518     6.9412     0.0000      10.218      18.266
facility_education          -0.0620     0.1456    -0.4260     0.6702     -0.3477      0.2236
facility_commercial          0.0834     0.1963     0.4248     0.6710     -0.3016      0.4683
facility_local_authority    -0.3135     0.3575    -0.8767     0.3808     -1.0147      0.3878
unemployment                 0.0004     0.0008     0.5545     0.5793     -0.0011      0.0020
greenspace_pct              -0.0214     0.0243    -0.8791     0.3795     -0.0691      0.0263
ptal                        -0.8847     0.5338    -1.6573     0.0977     -1.9316      0.1623
============================================================================================

===== Panel Results for Year6 group =====
                                    Parameter Estimates
============================================================================================
                          Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
--------------------------------------------------------------------------------------------
const                        25.620     3.4231     7.4845     0.0000      18.906      32.334
facility_education          -0.2060     0.2595    -0.7938     0.4274     -0.7149      0.3029
facility_commercial          0.1139     0.4124     0.2763     0.7824     -0.6949      0.9228
facility_local_authority     0.8620     0.3747     2.3004     0.0215      0.1270      1.5969
unemployment                -0.0015     0.0010    -1.5421     0.1232     -0.0033      0.0004
greenspace_pct              -0.1010     0.0406    -2.4875     0.0130     -0.1806     -0.0214
ptal                        -0.2622     0.8717    -0.3008     0.7636     -1.9718      1.4474
============================================================================================
```

5.5 SES Interaction Models

Introducing interactions between facility variables and unemployment (SES) (Table 6) shows no significant interaction effects in either age group, indicating SES does not substantially moderate facility impacts on obesity.

Table 6. SES Interaction Models Results (Both Age Groups Combined)

```
results_by_age_ses = {}

for group_name, outcome_var in age_groups.items():
    # Prepare data and create SES dummy and interaction terms
    data = panel_data.dropna(subset=[
```

```
        outcome_var, 'facility_education', 'facility_commercial',
'facility_local_authority',
        'unemployment', 'greenspace_pct', 'ptal'
    ]).copy()

    data['high_ses'] = (data['unemployment'] < data['unemployment'].median()).astype(int)
    data['edu_x_ses'] = data['facility_education'] * data['high_ses']
    data['com_x_ses'] = data['facility_commercial'] * data['high_ses']
    data['local_x_ses'] = data['facility_local_authority'] * data['high_ses']

    y = data[outcome_var]
    X = sm.add_constant(data[[
        'facility_education', 'facility_commercial', 'facility_local_authority',
        'unemployment', 'greenspace_pct', 'ptal',
        'edu_x_ses', 'com_x_ses', 'local_x_ses'
    ]])

    # Fit fixed effects panel model with clustered SE
    model = PanelOLS(y, X, entity_effects=True, time_effects=True)
    result = model.fit(cov_type='clustered', cluster_entity=True)
    results_by_age_ses[group_name] = result

    print(f"\n===== SES Interaction Results for {group_name} Group =====")
    print(result.summary.tables[1])  # Print coefficients table
```

```
===== SES Interaction Results for Reception Group =====
                                    Parameter Estimates
============================================================================================
                          Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
--------------------------------------------------------------------------------------------
const                        13.984     2.0549     6.8054     0.0000      9.9537      18.014
facility_education          -0.0632     0.1455    -0.4341     0.6643     -0.3485      0.2222
facility_commercial          0.1040     0.2005     0.5186     0.6041     -0.2893      0.4972
facility_local_authority    -0.3305     0.3902    -0.8471     0.3971     -1.0959      0.4348
unemployment                 0.0005     0.0008     0.6045     0.5456     -0.0011      0.0021
greenspace_pct              -0.0197     0.0243    -0.8092     0.4185     -0.0673      0.0280
ptal                        -0.8701     0.5327    -1.6335     0.1026     -1.9148      0.1747
edu_x_ses                    0.0463     0.0245     1.8889     0.0591     -0.0018      0.0944
com_x_ses                   -0.0323     0.0621    -0.5191     0.6038     -0.1541      0.0896
local_x_ses                  0.1009     0.1088     0.9273     0.3539     -0.1125      0.3142
============================================================================================

===== SES Interaction Results for Year6 Group =====
                                    Parameter Estimates
============================================================================================
                          Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
--------------------------------------------------------------------------------------------
const                        25.782     3.3853     7.6157     0.0000      19.142      32.422
facility_education          -0.2027     0.2563    -0.7906     0.4293     -0.7054      0.3001
facility_commercial          0.1466     0.4439     0.3302     0.7413     -0.7240      1.0171
facility_local_authority     0.8485     0.3752     2.2613     0.0239      0.1125      1.5845
unemployment                -0.0015     0.0010    -1.5632     0.1182     -0.0034      0.0004
greenspace_pct              -0.1033     0.0402    -2.5680     0.0103     -0.1822     -0.0244
ptal                        -0.2659     0.8688    -0.3061     0.7596     -1.9701      1.4382
edu_x_ses                   -0.0094     0.0557    -0.1687     0.8661     -0.1186      0.0998
com_x_ses                   -0.0697     0.1395    -0.4998     0.6173     -0.3433      0.2039
local_x_ses                 -0.0591     0.1921    -0.3076     0.7584     -0.4360      0.3177
============================================================================================
```

Overall, facility effects depend on age and type, with local authority facilities notably affecting older children. Socioeconomic and environmental variables, especially greenspace, emerge as robust determinants. Potential reverse causality regarding facilities warrants caution in policy interpretation.

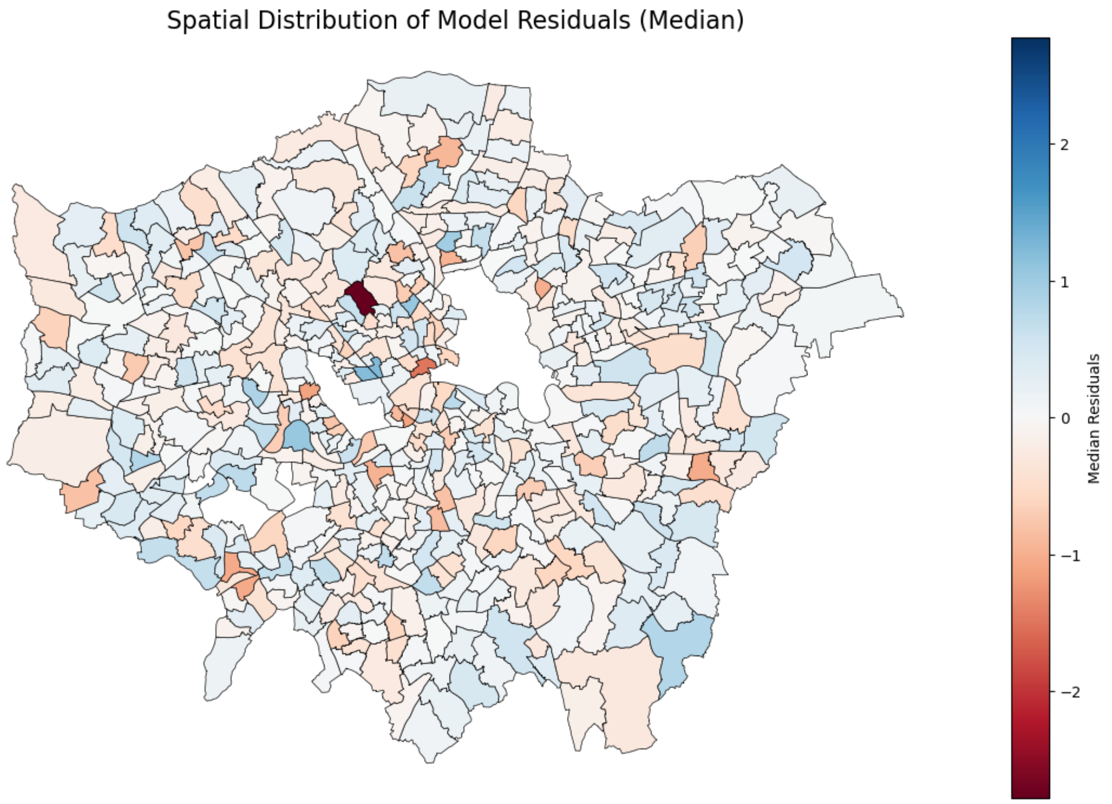
5.6 Residuals and Spatial Fixed Effects Analysis

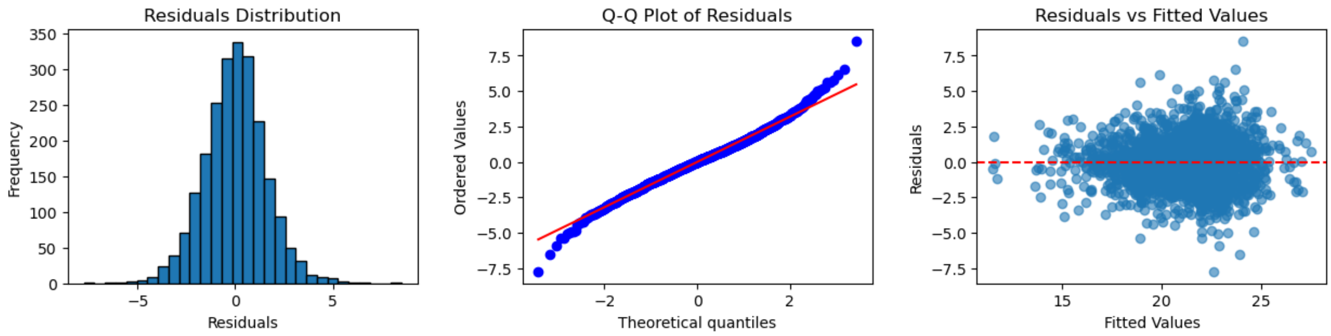
Residuals from the panel model are approximately symmetrically distributed around zero, with slight positive skewness (0.087) and moderate kurtosis (1.14) (Figure 5). The Q-Q plot shows near-normality with minor tail deviations, and residuals versus fitted values reveal no heteroscedasticity, supporting model validity.

Spatial mapping of median residuals at ward level indicates geographic clustering, suggesting spatial heterogeneity remains despite covariate and fixed effect controls.

```
# Calculate median residuals by ward for spatial plot
residuals = result_fe.resids
median_residuals = result.resids.groupby(level='ward_code').median()
wards_resid_gdf = wards[['GSS_CODE', 'geometry']].rename(columns={'GSS_CODE':
'ward_code'}).merge(
    pd.DataFrame({'ward_code': median_residuals.index, 'median_residual':
median_residuals.values}),
    on='ward_code')

# Plot spatial map of median residuals
wards_gem = wards[['GSS_CODE', 'geometry']]
wards_gem = wards_gem.rename(columns={'GSS_CODE': 'ward_code'})

vmax = max(abs(wards_resid_gdf['median_residual'].min()),
wards_resid_gdf['median_residual'].max())
```

```
```






```
Residuals Summary Statistics:
Mean: 0.000000
Standard Deviation: 1.602410
Skewness: 0.075269
Kurtosis: 1.213215
```

Figure 5. Residuals Distribution, Q-Q Plot, and Spatial Mapping of Median Residuals (Combined)

After accounting for spatial heterogeneity via ward-level fixed effects, the model (Figure 6) reveal substantial unexplained spatial variation in obesity rates, with notably higher effects in northern wards and lower effects in some southern areas.

```
# Extract ward-level fixed effects estimates from model results
entity_effects = result_fe.estimated_effects

# Convert MultiIndex to columns for easier processing
entity_effects_df = entity_effects.reset_index()

# Aggregate by ward_code to calculate average fixed effect per ward
```

```
entity_effects_grouped = entity_effects_df.groupby('ward_code')
['estimated_effects'].mean().reset_index()

# Merge aggregated fixed effects with ward geometries for mapping
wards_fe_gdf = wards_gem.merge(entity_effects_grouped, on='ward_code')

# Plot the spatial distribution of ward-level fixed effects
plt.figure(figsize=(12, 10))
wards_fe_gdf.plot(
    column='estimated_effects',
    cmap='coolwarm',
    linewidth=0.5,
    edgecolor='k',
    legend=True,
    legend_kwds={'label': 'Entity Fixed Effects'}
)
plt.title('Ward-level Fixed Effects Distribution')
plt.axis('off')
plt.tight_layout()
plt.show()
```

```
<Figure size 1200x1000 with 0 Axes>
```

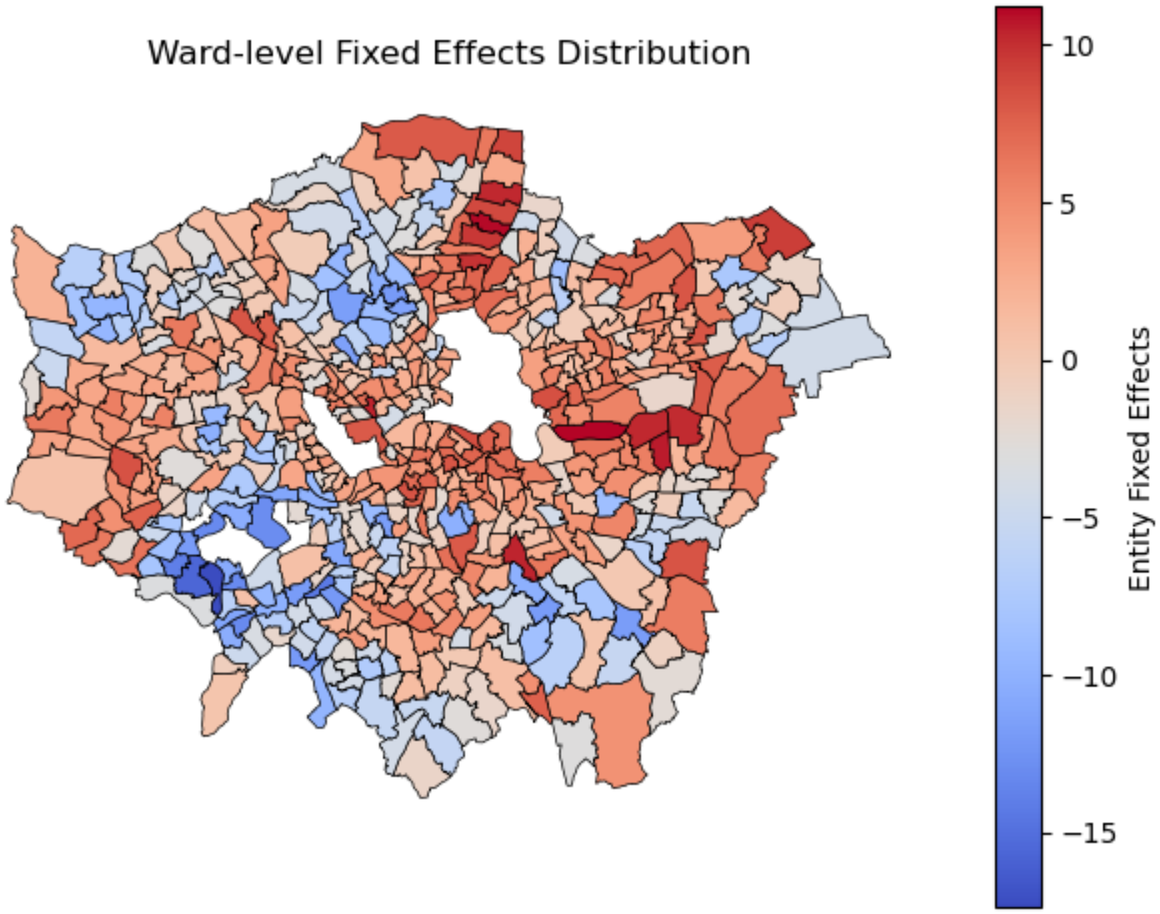


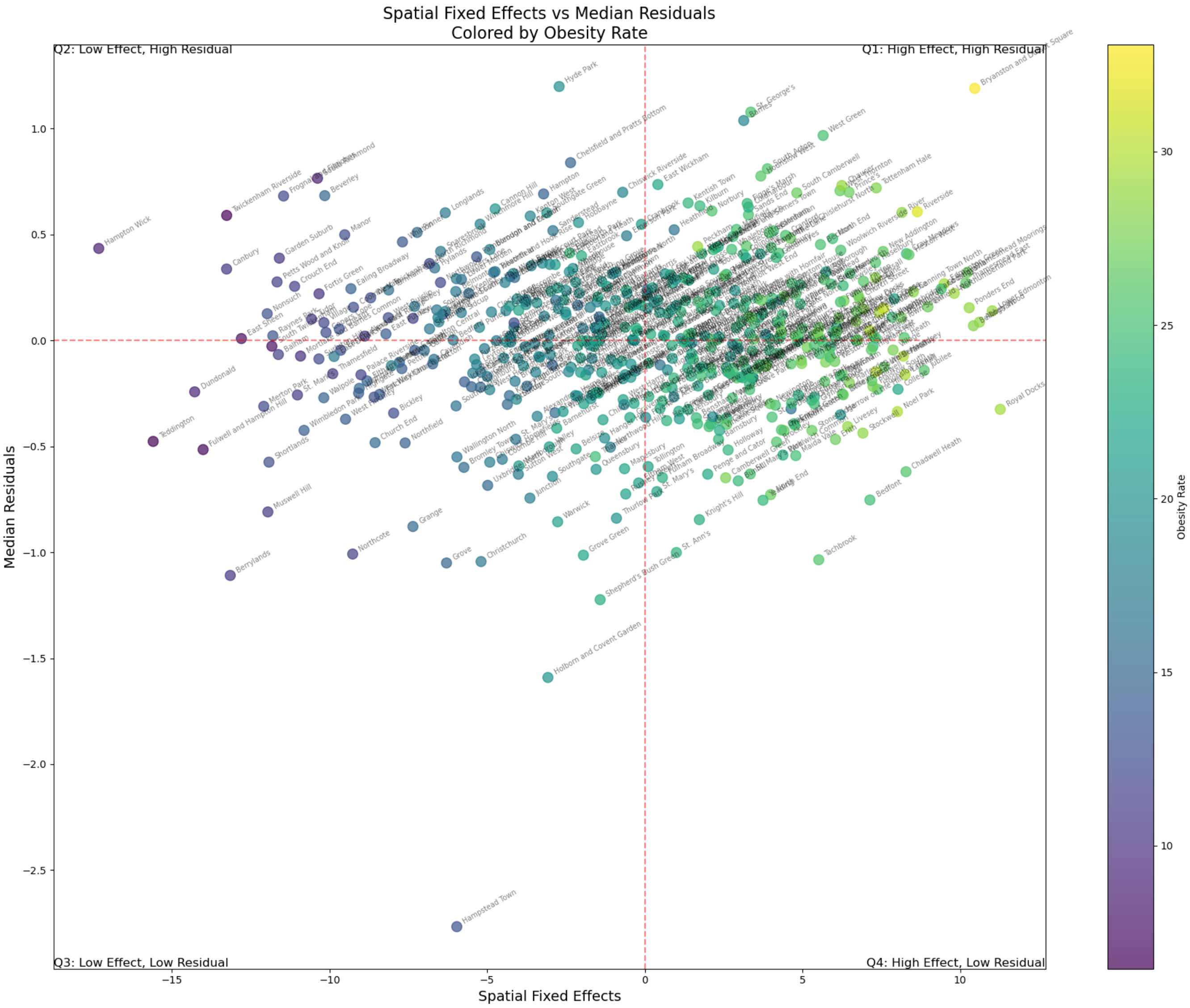
Figure 6. Ward-Level Fixed Effects from Panel Model

Subsequently, a quadrant plot (Figure 7) combining spatial fixed effects and mean residuals with ward labels demonstrates wards with high spatial effects correspond to higher obesity rates, reflecting strong localized influences captured by the model.

Residuals are less systematically linked to obesity, as wards with similar residuals show diverse obesity levels, implying other unobserved, possibly non-spatial or softer policy factors. While spatial fixed effects explain much variation, further research into these complex determinants is recommended.

```
# Aggregate spatial fixed effects and mean residuals by ward_code
spatial_effects = result_fe.estimated_effects.groupby(level='ward_code').mean().squeeze()
median_residuals = result_fe.resids.groupby(level='ward_code').median()

# Calculate mean obesity rate and get ward names
obesity_rates = panel_data.groupby('ward_code')['obesity_year6'].mean()
ward_names = panel_data.groupby('ward_code')['ward_name'].first()

# Prepare dataframe combining all key variables
plot_df = pd.DataFrame({
    'ward_code': spatial_effects.index,
    'ward_name': ward_names.reindex(spatial_effects.index),
    'spatial_effects': spatial_effects.values,
    'median_residuals': median_residuals.reindex(spatial_effects.index).values,
    'obesity_rate': obesity_rates.reindex(spatial_effects.index).values
})

# Define median thresholds to classify quadrants
med_spatial = plot_df['spatial_effects'].median()
median_residuals = plot_df['median_residuals'].median()

def assign_quadrant(row):
    if row['spatial_effects'] >= med_spatial and row['median_residuals'] >=
median_residuals:
        return 'Q1: High Effect, High Residual'
    elif row['spatial_effects'] < med_spatial and row['median_residuals'] >=
median_residuals:
        return 'Q2: Low Effect, High Residual'
    elif row['spatial_effects'] < med_spatial and row['median_residuals'] <
median_residuals:
        return 'Q3: Low Effect, Low Residual'
    else:
        return 'Q4: High Effect, Low Residual'

plot_df['quadrant'] = plot_df.apply(assign_quadrant, axis=1)
```

```
```




```
Quadrant Summary:
                                Ward Count  obesity_rate  spatial_effects  \
quadrant
Q1: High Effect, High Residual         144     24.938825         4.549429
Q2: Low Effect, High Residual          140     17.678274        -4.335078
Q3: Low Effect, Low Residual           143     17.648077        -4.406520
Q4: High Effect, Low Residual          140     24.573536         4.141186

                                median_residuals
quadrant
Q1: High Effect, High Residual          0.221822
Q2: Low Effect, High Residual           0.196789
Q3: Low Effect, Low Residual           -0.241363
Q4: High Effect, Low Residual          -0.168691
```

Figure 7. Quadrant Plot: Spatial Fixed Effects and Mean Residuals by Ward

7. Discussion and Conclusion

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