
Revealing Childhood Obesity Differentials to Identify Effective Intervention Strategies for Local Authorities in England

1. Introduction

Childhood obesity and its severe health and social consequences have become a common concern in society and add urgency to the need for effective intervention strategies (Han, Lawlor and Kimm, 2010; Brennan *et al.*, 2011). Meeting this need requires identifying the characteristic of the childhood obesity epidemic; and evaluating the effectiveness of interventions to locate emerging strategies (Boehmer *et al.*, 2008).

Limited studies focused on local authority's policy strategies on childhood obesity prevention. In this research, we attempt to reveal characteristics of childhood obesity differential at local authority level and quantify influences of allocated budget areas on the decline in childhood obesity rate.

2. Data and methods

Our analysis starts with childhood obesity cases data of 152 local authority areas across the country in three-time points, combined with local authority level budget allocation on controlling childhood obesity and population data. All these data are collected from the Department of Health. Tukey fences are employed to detect outlier in the data.

To remove the scale effect of population, we calculate the childhood obesity rate (COR) for each local authority at each time point, which converts the childhood obesity into a standardized metric and facilitates comparisons across regions and over time. The change in childhood obesity rate (CCOR) during the study period (Eq. 1) are used to conduct statistical analysis and modelling.

$$CCOR = \left(\frac{\text{Cases in } T_2}{\text{Population in } T_2} - \frac{\text{Cases in } T_1}{\text{Population in } T_1} \right) \times 1000\% \quad (1)$$

We first investigate the relationship between childhood obesity cases and population to observe the difference across scale (Bettencourt *et al.*, 2007; Bettencourt, 2020). And then use the COR in three-time points to capture the variation over time.

Finally, we adopt a multivariate regression analysis to assess the association between CCOR and budget areas. This regression analysis can help us understand the influences of different parts budget on CCOR, and we take the logarithm of each budget amount to scale all explanatory variables in a similar magnitude. A categorical variable (Region) is introduced to capture the regional difference. The full model is taking the form of Eq. 2.

$$CCOR = \beta_0 + \sum \beta_{1i} \times \text{Log}(\text{Budget}_i) + \sum \beta_{2k} \times \text{Region}_k + \varepsilon \quad (2)$$

We use the least-squares method for model estimation. Percentage changes of the CCOR caused by one standard deviation increase of the explanatory variable are employed to compare the influences of explanatory variables (Xu *et al.*, 2020). We also calculate the variance inflation factor (VIF) for each explanatory variable to test the multicollinearity. Python 3.8 is used to conduct all statistical analysis, calculation and visualization.

3. Results

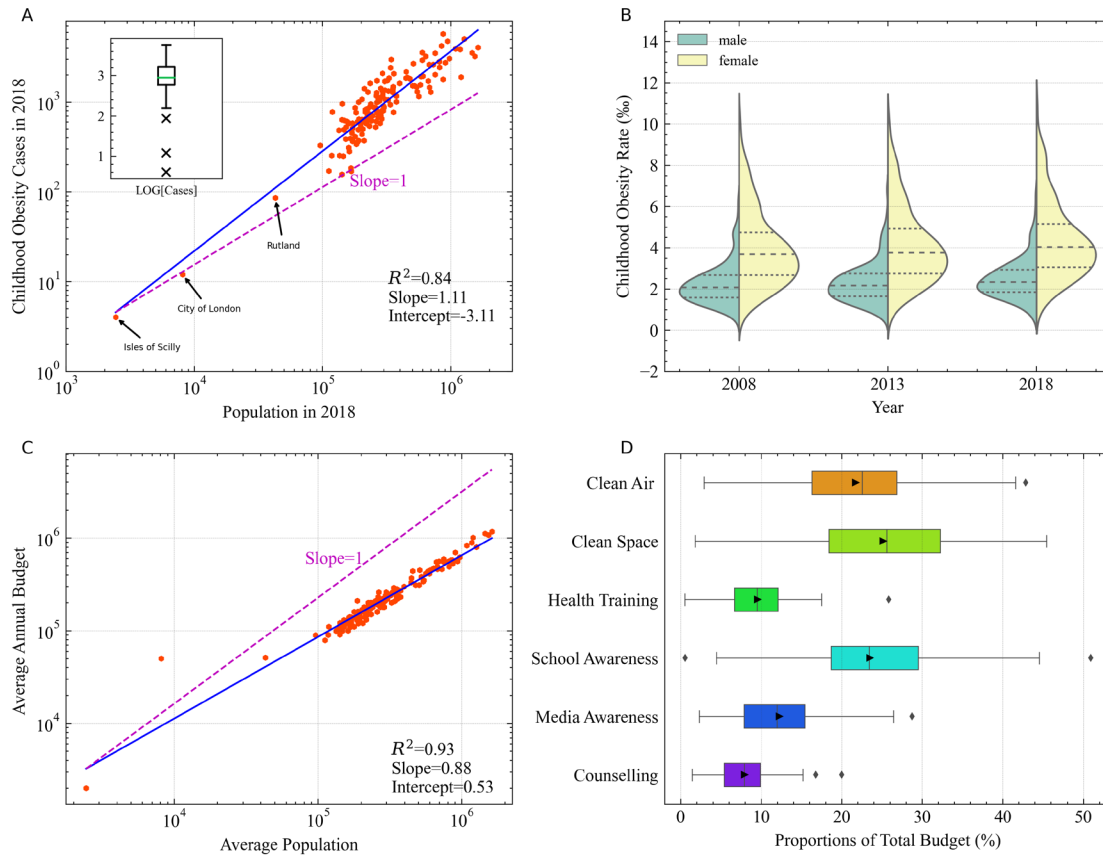


Fig. 1. Statistics characteristics of indicators relevant to childhood obesity.

Childhood obesity cases follow scaling relationship significantly (Fig. 1A), which has a scaling exponent greater than 1. It means that as population increases, cases increase more than the expected linear growth. However, the distribution of the total budget shows a sub-linear relationship with the population (Fig. 1C), meaning that the more people the authority has, the smaller the per capita annual budget instead, suggesting an unfair budget strategy. Meanwhile, the mean value of the COR in 2008 was 3.11%, while the mean value of the COR in 2018 increased to 3.47%. The violin plots of childhood obesity rate further reveal the distinct increase in childhood obesity. Moreover, females have a higher COR than males, and variation of different local authorities in female obesity rate are much more significant than it in male (Fig. 1B). In these analyses, three outliers were detected, and two of them were removed based on the distribution of childhood obesity cases.

As we use different budget areas as explanatory variables, the CCOR as the explained variable to build multivariate regression model, regression results of 150 samples are shown in Table 1. The adjusted R^2 is 0.897, which means that budget areas and regional differences can explain about 90% variance of CCOR. The VIFs for all explanatory variables are less than 4, indicating there is little collinearity. Four explanatory variables in the model pass the t-test at a significant level of 0.001.

We then check the residual plot of the regression results (Fig. 2). The residuals are not changing with the fitted value, normally distributed and have nearly equal variance, indicating that the residuals are independent, the error is normally distributed, and the errors have equal variance. All these verify the regression model meets the assumptions.

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Table.1 Multivariate regression results with the CCOR (‰) from 2008 to 2018 as the explained variable (N = 150#, adjusted R² = 0.897).

Explanatory variables	Statistic metrics				
	Coefficient	Standard error	p-value	t	VIF
(Constant)	0.162	0.219	0.461	0.740	-
Clean Air	-0.051*	0.020	0.012	-2.534	1.990
Clean Space	0.013	0.019	0.502	0.672	1.837
Health Training	0.025	0.020	0.200	1.288	1.837
School Awareness	-0.099***	0.021	0.000	-4.725	1.929
Media Awareness	0.088***	0.022	0.000	4.089	2.257
Sub Counselling	0.035	0.023	0.127	1.537	2.672
<i>East of England</i>	-0.015	0.062	0.809	-0.242	2.077
<i>London</i>	0.484***	0.055	0.000	8.841	3.947
<i>North East</i>	0.181**	0.064	0.005	2.839	2.346
<i>North West</i>	0.295***	0.056	0.000	5.254	3.226
<i>South East</i>	-0.033	0.059	0.579	-0.557	2.998
<i>South West</i>	-0.039	0.061	0.520	-0.644	2.618
<i>West Midlands</i>	0.075	0.063	0.239	1.183	2.660
<i>Yorkshire and the Humber</i>	0.207**	0.062	0.001	3.333	2.715

67 *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

68 We further analyze the regression results. Holding all other explanatory variables
69 as constant at their means, we calculate the percentage change of the CCOR when one
70 explanatory variable increase by one standard deviation. As a result, one standard
71 deviation increases in the parts of the budget allocated to improving air quality and
72 raising awareness in schools slows down the increase of COR by 11% and 20%,
73 respectively. Moreover, one standard deviation increases in the part of the budget
74 allocated to raising awareness through the media accelerate the increase of COR by
75 19%. Although statistically insignificant, other parts of budgets show a negative effect
76 on controlling the increase in COR. However, the data on the percentage of budget
77 allocation shows that 40-60% of the total budget is allocated to those budget areas that
78 do not contribute to the controlling of COR (Fig. 1D).

79 In terms of regional differentials, local authorities in London have more increased
80 on COR by 0.484 than non-London regions with the same budget allocation over the
81 last ten years, which is 2.35 times the average obesity rate change. Regions in the north
82 of England have more increases on childhood obesity rate than regions in the south of
83 England by 0.2 to 0.3, which is 60 to 80 percentage more of the average change.

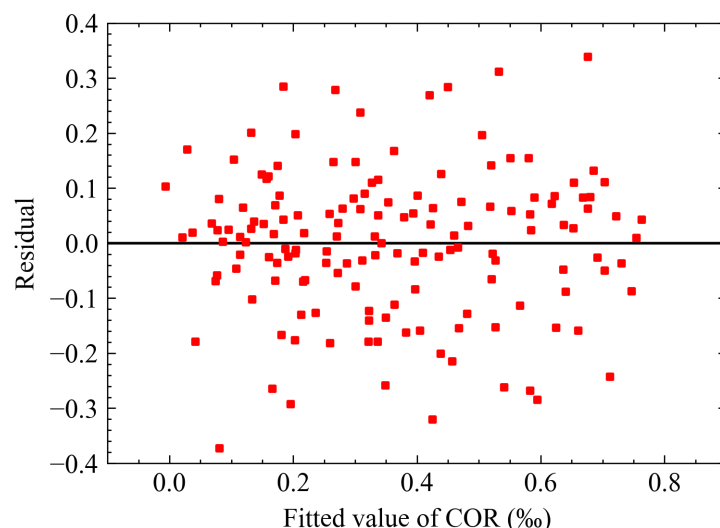


Fig. 2. Residual plot of the regression result

4. Discussion and conclusion

These results imply that governments should focus their efforts to control childhood obesity on local authorities with larger populations or in the north of England and that more attention should be paid to childhood females. For local authorities, the budget should allocate on areas that have a positive effect on slowing down the increase in obesity rates, such as raising awareness in schools, with less allocation to other areas such as raising awareness through the media. Previous budget strategies have proved to be grossly unbalanced and unfair.

Our analysis is limited due to the data absence of childhood population, as the change of demographic structure may cause the increase of COR calculated in this study. Meanwhile, sex ratio and scale-adjusted metrics need to be taken into consideration (Alves *et al.*, 2015).

(Word count : 982)

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