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Accounting for socio-economic inequalities in health to inform SDG decision making: A proof-of-concept study

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ABSTRACT

Most SDG-inequality indices rely on a unidimensional design which cannot reflect how a given health outcome is distributed along the socio-economic spectrum. The concentration index can overcome this limitation. With an application to adult excess weight data, the concentration index was illustrated along with a decomposition method which allowed for key predictors to be identified. An Erreyger's concentration index and Shapley decomposition-based approach provide a relatively simple analytical tool to the monitoring of socio-economic inequalities in health. Such analytical approach should be considered as a monitoring tool by public managers to inform SDG policy and budgetary decisions.

Introduction

With its 2030 Agenda, the United Nations set out 17 interrelated Sustainable Development Goals (SDGs), mapping the major challenges society is currently facing and calling on public and private sector stakeholders to adopt actionable solutions to tackling them [1]. Recognising its centrality for achieving sustainable development, the 2030 Agenda identified safeguarding population health and reducing unfair and unjust inequalities (i.e., inequities), within and across countries, as a key priority [2]. Evidence has showed that a social gradient exists along the socio-economic spectrum, manifesting in stark differences in mortality and chronic disease risks, disproportionately impacting those at lower income level, educational attainment, occupational status and living in the most deprived neighbourhoods [3–6].

A major, potentially preventable driver of chronic disease risk, including type II diabetes [7], cardiovascular [8] and respiratory disease [9] and cancer [10], and productivity loss [11], is excess weight. The World Health Organization defines adult overweight and obesity as abnormal or excessive weight, typically measured at population level in terms of body mass index (BMI). The BMI threshold for adults is 25 for overweight and 30 kg/m^2 for obesity [12]. In the United Kingdom only, the annual direct health care cost from treating complications related to obesity has been estimated to be over £6 billion, with wider societal costs of £27 billion [13]. And these annual cost estimates are expected to increase in the future, along with the global prevalence of obesity which is on the rise, nearly tripling since 1975 [14] and affecting disadvantaged communities the most [15].

Following the transfer of responsibilities for public services - including public health and health care - from central governments to elected authorities at the local level, local governments (LGs) such as city councils in Australia [16], municipal governments and counties in the US [17], concejos municipals in Mexico and Colombia [18], and local authorities in Ireland [19] and the United Kingdom [20] have a fundamental role to play in tackling health inequities. To support LGs in pursuing sustainable development strategies and aid evidence-based policies aimed at addressing key preventable determinants of health inequalities, such as obesity, international commitment has been advocated and expressed in the form of roadmaps and guidance [21]. Among other essential prerequisites, the monitoring of progress against SDG targets presents a key consideration although, in practice, often also a technical obstacle due to the limited resources available to LGs in terms of data analysis capabilities [22].

Adequate monitoring is crucial for timely informing health managers and ultimately supporting the design of sound strategies and programmes. To this end, a great deal of monitoring measures have been endorsed by global initiatives [23] and international authorities to monitor progress against SDG targets [24]. Performance indicators available in the public domain range from summary metrics to more complex composite indicators, notably, the SDG index [25]. This index builds on the methodology of the Sustainable Development Report to track countries' performance on the 17 SDGs and identify policy priorities. The index score can be interpreted as expressing the achievement on the SDGs, with the difference between score and 100 showing the distance in percentage points that needs to be achieved to attain optimal

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performance on the target.

Borrowing from the income inequality literature, the SDG index and other composite indices used to monitor progress against SDG targets, such as the LNOB [26], seemingly incorporate inequality measures that are designed based on a Gini index approach. The Gini index, or Gini co-efficient, is a well-established measure which can be used to quantify the distribution of a given ratio-scale variable, such as income or wealth, across a population in a single value ranging from 0 to 1, with 0 representing perfect equality (all individuals in the population have the exact same income or wealth) and 1 representing perfect inequality (one individual owns all the income or wealth) [27]. However, in common with other widely used inequality indices such as the Palma ratio [28] and the Atkinson index [29], the Gini index is a unidimensional index. Unidimensional indices measure how a certain outcome is distributed across a population along the same dimension [30], hence they cannot reflect how said dimension is distributed along another dimension, such as socio-economic spectrum is which is in fact the focus of public health policy [31].

In addressing the limitations of using unidimensional approaches to measuring health inequalities, a question emerges on what monitoring tool should be used to enable LGs monitoring socio-economic inequalities in health al the local population level and therefore informing local SDG decision making. This article presents a proof-of-concept study to illustrate the applicability and usefulness of the Erreygers' concentration index (ECI) and respective decomposition analysis to address the following research question: what analytical framework should be used for monitoring socio-economic inequalities in health and inform SDG decision making?

A family of rank-dependent inequality indices which can enable researchers to analyse socio-economic inequalities in health is that of concentration indices [32]. With these indices, every individual's level of health (or ill-health, such as excess weight) and every individual's rank along the socioeconomic spectrum is considered. Relevant guidance has been provided to support appropriate index selection which ought to be based on the index' specific mathematical properties and consequent underlying value judgements [33].

As a generalised concentration index, the Erreyger's concentration index (ECI) measures the degree of absolute inequality between socio-economic groups – with translation-invariance property, whereby adding the same "amount" - e.g., one BMI point - to everyone's baseline level leaves the index value unchanged - and it has been recommended and most frequently applied for the study of bounded health variables such as BMI [34]. Of the ECI's mathematical properties, decomposability and subgroup consistency are of particular importance as they enable measurement of the contribution of specific subgroups to overall (ill) health inequality in a population. In fact, interplays between contributing factors are likely to occur, such as between individual-level and environmental characteristics [35], which can also play different explanatory roles depending on the level of ill health severity considered [36]. In this paper, we apply this analytical approach to longitudinal data from a representative sample of adults in England and examine trends and determinants of socio-economic inequalities in excess weight.

Materials and methods

The Erreyger's concentration index

The implications of the bounded nature of the outcome variable (excess weight in this study) for the concentration index have been thoroughly discussed in the literature, with a few correction methods being proposed [37]. However, the Erreyger's correction method has been recommended for cardinal health variables [33] such as BMI and previously used in empirical studies of health inequalities [38]. The ECI measures the level of absolute inequality in the outcome variable across the distribution of socio-economic status.

The Erreygers' CCI can be expressed formally as:

$$\mathrm{ECI} = \frac{4 * \mu}{b - a} * \frac{2 * \mathrm{cov}\ (\mathrm{yi},\ \mathrm{ri}\ )}{\mu}$$

where yi is the BMI measure for each individual (i), μ represents the mean BMI value, ri is the individual's fractional rank along the socio-economic distribution of interest, cov denotes the covariance, and a and b are the lower and higher bounds of the excess weight measure. The CCI can range between −1 and 1, and a positive value indicates that the burden of excess weight is disproportionately borne by the most deprived individuals, and vice versa.

Decomposition analysis

To quantify the independent effect of key factors contributing to the observed socio-economic deprivation-related inequalities in excess weight, we used the Shapley decomposition method [39]. Decomposition analyses were performed at the mean, as well as across the excess weight spectrum, that is considering inequalities in overweight (BMI≥25), obesity (BMI≥30) and morbid obesity status (BMI≥35). The Shapley method enables analysts to evaluate how control variables independently contributed to the explained variance, and therefore assess their relative importance to the estimated inequalities. This method computes marginal effects by eliminating each covariate in sequence and then assigns to each factor the average of its marginal contribution in all its possible elimination sequences.

Data and variables

Individual-level survey data on excess weight from a representative sample of 83,447 adults in England were analysed. The Health Survey for England is an annual repeated cross-sectional survey of private households, which gathers information on respondents' socio-demographic characteristics (e.g., age, gender and socio-economic deprivation) and their health and lifestyle status [40]. Longitudinal changes in BMI across population sub-groups were estimated from the 2009–2019 waves, including individuals aged at least 20 years old and with a valid (interviewer-assisted) BMI measurement in the analyses [41].

The index of Multiple Deprivation (IMD) quintile was selected at the socio-economic dimension of inequality. This measures relative levels of deprivation within neighbourhoods in England - with an average of approximately 1500 residents or 650 households - and is organised across seven domains of deprivation which are combined and weighted (income, 22.5 %; employment 22.5 %; health deprivation and disability, 13.5 %; education, skills training 13.5 %; crime 9.3 %; barriers to housing and services 9.3 %; living environment 9.3 %) [42].

To adjust for survey non-response, we applied a set of weights within HSE for the different elements of the survey. For 17.1 % of survey respondents (n = 14,294), BMI measurement values were missing. To correct for this source of selection bias, we applied an inverse probability weighting (IPW) method, in line with the approach used within Health Survey for England [41]. To further adjust for imbalances between the sampling quotas and the final survey samples, post-stratification weights were constructed using the IPW-derived weights and a raking procedure [43].

Statistical analysis

Annual changes in mean BMI and BMI distribution by IMD quintile were first examined graphically. Based on previous studies [35,36,38], seven age groups for men and women were considered for heterogeneity analysis. Pooled regression analyses were performed to test for significant linear trends in BMI change within and between sub-groups.

A synthetic control approach (also referred to as 'pseudo-panel') was used to estimate 'cohort-specific' trajectories of mean BMI change over time. This is a statistical technique for estimating 'fixed-effects' models, which has been previously applied in epidemiological studies of population obesity that can be used when repeated cross-sectional data are available [44]. Synthetic cohorts were created by matching cohorts by birth, gender and IMD. Due to the age variable being available only by five-year categories from wave 2015 onwards [41], changes in BMI were determined for the same matched cohorts in two separate five-year time periods that is, between 2009 and 2014 and between 2014 and 2019.

Ordinary least squares and unconditional quantile regression models were estimated to identify key predictors of change in mean BMI and BMI distribution, respectively. A backward stepwise approach for model specification was employed to reduce the risk of omitted variable bias [45]. Interaction terms were used to evaluate the presence of effect modification. Statistical significance was set at $p < 0.05$. All analyses were performed using STATA 16 software [46].

A forward stepwise approach for model specification was employed, with three models being built progressively. Specification 1 included intrinsic individual characteristics, namely, age, gender and ethnic background. This specification was then enhanced by considering individual's personal circumstances, namely, whether they had long-lasting limiting illness, their marital status and urbanicity (e.g., they lived in an urban area or not, specification 2). The full specification was further augmented by the socio-economic deprivation dimensions. Model selection was based on the Bayesian information criterion [47].

Results

Trends in excess weight inequalities

Fig. 1 compares observed time trends in mean BMI by IMD quintiles and shows that, unlike the remaining of the population, adults living in the least deprived neighbourhoods in England did not gain weight over the 2009–2019 period. Conversely, starting at an increasingly higher baseline BMI value, individuals living in more deprived neighbourhoods have increased their BMI score at an increasingly higher rate, disproportionally so those living in the most deprived areas.

Breaking down the linear predictions illustrated in Fig. 1 and testing for statistically significant trends, Table A1 (Appendix A) shows that both the least and second least IMD deprived neighbourhoods did not increase their body weight significantly over the studied period. Compared to the least deprived, the top three most deprived IMD areas showed an increase in mean body weight, with differences in trends emerging nonetheless. The intermediate quintile increased BMI significantly over the first five years (2009–2014, mean BMI change: 0.640, $p = 0.013$) only, whereas the top IMD quintile showed no BMI increase within the same period (mean BMI change: −0.008 $p = 0.980$) – whilst reporting a highly significant and large increase over the following five years (mean BMI change: 1.295 $p < 0.001$).

A marked level of variability in mean BMI change was also observed between genders and age groups (Table A1, Appendix A). An older age was consistently associated with a higher BMI linearly until the 70–79 years of age, after which body weight gradually declined, yet remaining above that of the 20–29 years old groups. Only the group of 60–69 years old gain weight significantly over the 2009–2014 period (mean BMI change: 0.543, $p = 0.035$), while the two youngest subgroups of adults did so within the 2014–2019 period (20–29 years old, mean BMI change: 0.778, $p = 0.016$; 30–39 years old, mean BMI change: 0.775, $p = 0.003$). Neither men or women increased their body weight significantly after the first five years, whereas a significant increase was estimated for both sexes in the subsequent period (men, mean BMI change: 0.441, $p = 0.003$; women, mean BMI change: 0.370, $p = 0.018$).

Cohort trajectories of excess weight inequalities

Table 1 below shows the results of the pseudo-panel analysis conducted by matching samples by birth. Overall, the ten-year results indicate that adults living in England increased their body weight at a declining rate as they aged. This occurred within the youngest three cohorts (20–49 years old), after which their BMI score remained stable until they the age of 75 when they started losing weight.

These patterns of BMI change were comparable between men and women, except that the latter group showed significant increases in

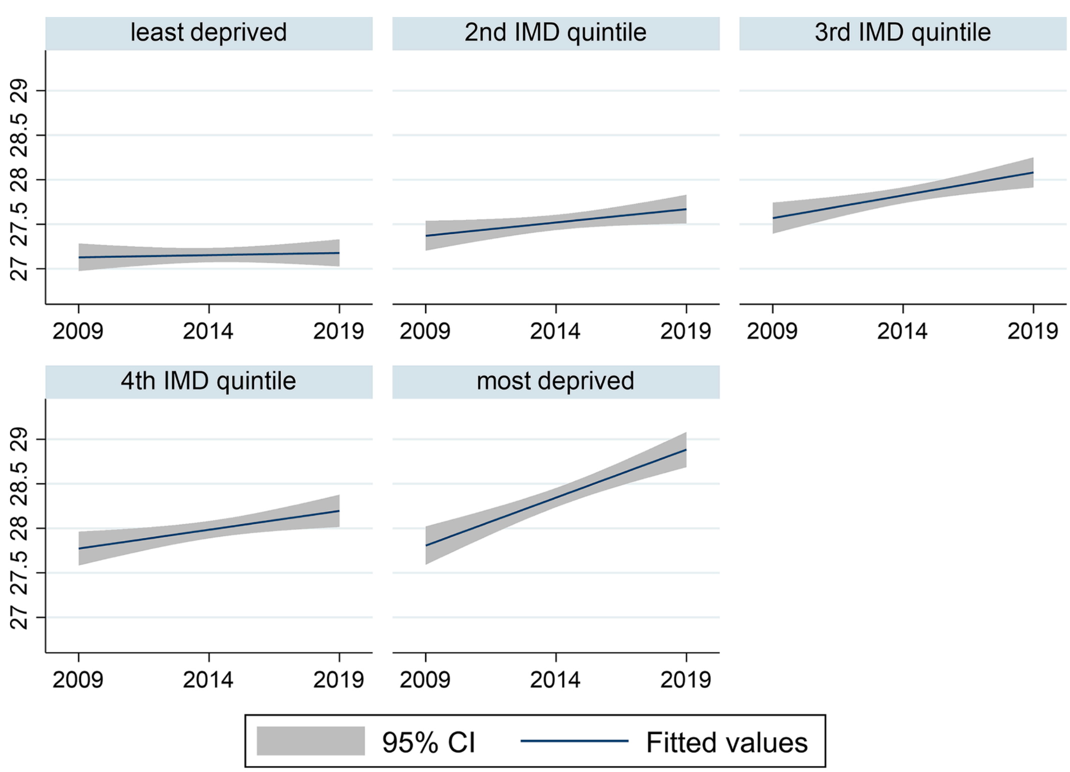

Fig. 1. IMD-related gradient in mean BMI trends.

Table 1
Cohort trajectories in mean BMI.

	2009 cohort	Δ BMI 2009–2014 Mean	SE	Δ BMI 2014–2019 Mean	SE
	20–29	1.139[a]	0.311	1.302[a]	0.278
	30–39	0.907[a]	0.260	0.930[a]	0.243
	40–49	0.425[c]	0.254	0.388[c]	0.231
	50–59	0.201	0.287	−0.102	0.251
	60–69	0.111	0.255	0.33	0.246
	70–79	−0.055	0.317	−0.857[a]	0.324
	80+	−0.610	0.521	0.139	0.825
Men	20–29	1.495[a]	0.422	1.272[a]	0.411
	30–39	1.325[a]	0.337	0.496	0.333
	40–49	0.236	0.323	0.339	0.298
	50–59	−0.081	0.397	0.109	0.336
	60–69	−0.318	0.313	1.062[a]	0.308
	70–79	0.225	0.403	−1.067[a]	0.394
	80+	0.189	0.597	−1.610[b]	0.760
Women	20–29	0.743	0.462	1.334[a]	0.375
	30–39	0.469	0.396	1.371[a]	0.354
	40–49	0.606	0.391	0.436	0.353
	50–59	0.472	0.412	−0.319	0.373
	60–69	0.519	0.397	−0.336	0.374
	70–79	−0.344	0.482	−0.667	0.499
	80+	−1.376[c]	0.790	−1.482	1.245
IMD non-deprived	20–29	1.115[a]	0.347	1.149[a]	0.323
	30–39	1.015[a]	0.270	0.679[c]	0.262
	40–49	0.663[b]	0.266	0.084	0.249
	50–59	0.303	0.301	−0.389	0.272
	60–69	−0.145	0.272	0.237	0.254
	70–79	−0.104	0.340	−0.789[c]	0.340
	80+	−0.270	0.496	−0.372	0.851
IMD deprived	20–29	1.178	0.685	1.940[a]	0.554
	30–39	0.633	0.672	1.958[a]	0.609
	40–49	−0.705	0.735	1.817[a]	0.596
	50–59	−0.387	0.866	1.463[b]	0.634
	60–69	1.487[b]	0.716	0.916	0.804
	70–79	0.430	0.863	−1.450	0.946
	80+	−3.881	2.585	5.024	2.314

[a] $p < 0.01$,.
[b] $p < 0.05$,.
[c] $p < 0.1$.

mean BMI among the two youngest cohort only within the 2014–2019 period. Breaking down these estimates by IMD status, these population-level patterns were generally followed by adults living in the bottom four highest quintiles of deprivation, whereas the most deprived showed upward trajectories including within the 50–59 cohorts and exclusively in the latter five-year period.

Trends of inequalities in excess weight distribution

Fig. 2 compares the baseline BMI distribution (2009) with that observed after five and ten years over the across IMD quintiles. Overall, this figure shows that the BMI baseline distribution gradually flattens with an increasingly more marked right skew, as the level of deprivation increases. This meant that, compared to the least deprived, an increasingly lower proportion of adults concentrated around the modal BMI value and that a higher proportion of obese and morbidly obese individuals was present among those more deprived. In longitudinal terms, this pattern occurred within each IMD quintile, but more markedly within the most deprived IMD areas where the BMI mode shifted to the right, closer to the 30 BMI value.

These visual observations were tested statistically and are shown in Table 2. Overall, no significant changes in the BMI distribution occurred over the 2009–2014 period, except within adults living in the intermediate IMD quintile where a positive shift, particularly at 75th or higher percentiles of the BMI distribution was observed. Over the following five-year period, strong evidence was found for a significant increase in BMI from the top most deprived areas, which was driven disproportionally by upward changes at the higher BMI percentiles (95th percentile: 3.069, $p < 0.001$; 99th percentile: 6.684, $p < 0.001$), widening the inequality in excess weight accordingly.

Comparably, no significant changes in BMI distribution were observed in the first five years for any gender or age groups, expect the 60–69 subgroup who followed a pattern of change in excess weight similar to that of the 3rd IMD quintile. In the 2014–2019 period, the two youngest subgroups (20–29, 30–39) only showed a significant and comparable increase in BMI, which was particularly pronounced at the 75th percentile. A smaller overall increase was observed both within men (mean 0.441, $p = 0.003$) and women (mean 0.370, $p = 0.018$), which was unequally distributed however. The mean increase was mostly driven from within the 75th and 90th percentiles in men, whereas an increasingly larger contribution from higher BMI percentiles occurred within women.

Factors contributing to excess weight across the BMI spectrum

Table B1 (Appendix A) compares the linear regression analysis results conducted at 'at the mean' versus those across selected BMI quintiles. Firstly, the average increase in the BMI gap observed over time between the IMD most deprived and the remaining of the population was shown to be driven by incrementally larger changes from above the median value at the higher quantiles of the BMI distribution. This confirmed that, over time, the number of adults living with obesity and severe obesity increase disproportionally more from within the most deprived areas, related to the rest of the country. After full adjustment, an older age until 70 years old seemed to play a clear role within the overweight segment of the distribution only (positive linear relationship), whereas obese and severely obese women reported significantly higher BMI scores than men, while the opposite was the case for overweight.

Having a limiting longstanding illness was the predictor consistently and most strongly associated with higher BMI, accumulating an increasingly higher contribution to BMI when moving to higher distribution quantiles. Being of a black ethnicity was showed to be associated with a higher BMI within overweight status, but not within obesity, while an Asian ethnicity was consistently associated with lower BMI values, relative to a white ethnic background. Region of residence was showed to have a significant effect on BMI score only within the 50–75th quantiles, with the North-Eastern region scoring either equally or higher than the remaining eight regions, whereas educational qualification had a more consistent effect along the BMI spectrum. Specifically, compared to the highest qualification, a lower education level as positively associated with BMI, with no qualification being consistently and more strongly associated with higher BMI values along the whole BMI distribution.

Discussion

This paper is concerned with the issue of local monitoring of socio-economic inequalities in health dynamics and goals to inform SDG-related policy and budgetary decisions. Based on an application to adult excess weight, this proof-of-concept study illustrated the suitability and usefulness of a Erreyger's concentration index and quantile decomposition-based approach which address some of the key limitations common to unidimensional indices of health inequality. The presented analytical approach provides ample flexibility to i) choose the socio-economic dimension of interest ii) adopt a nuanced approach to the identification of key inequality drivers on average, as well as along the health outcome spectrum. Whereas several SDG monitoring metrics are publicly available mostly at a country level, this analytical approach can be tailored to accommodate local policy context needs and priorities and presents a relatively easy-to-use tool to inform evidence-based health management decisions.

For illustration, this analytical approach was applied to the study of neighbourhood deprivation-related inequalities in adult excess weight

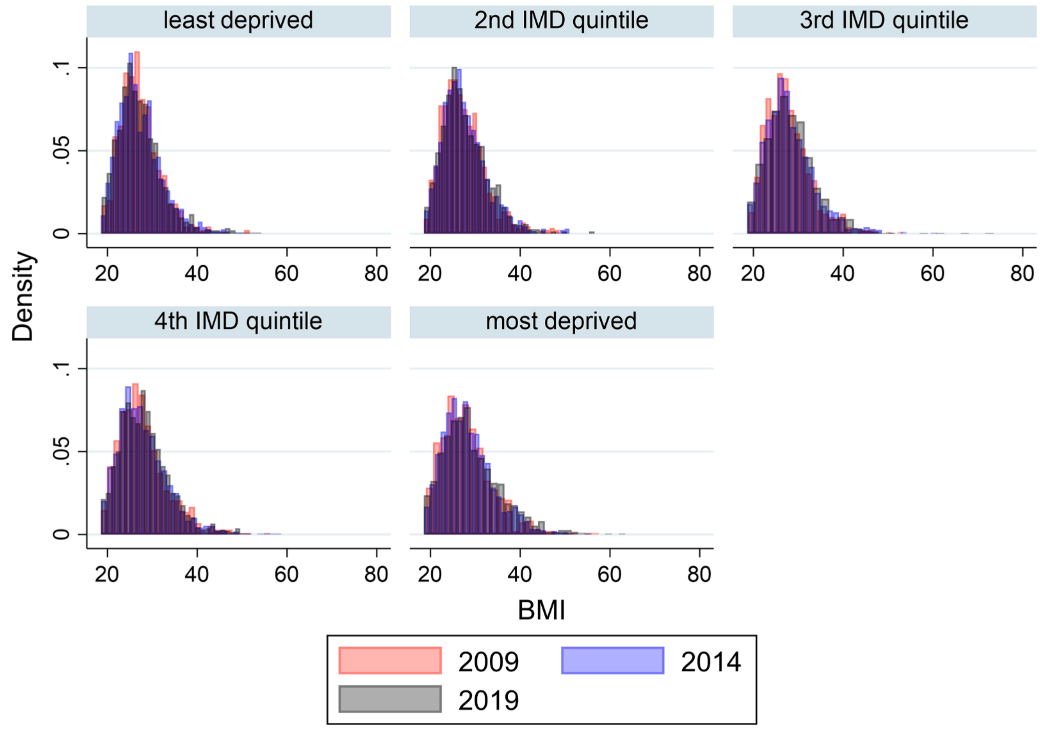

Fig. 2. Trends of inequalities in excess weight distribution.

Table 2
Unadjusted ordinary least square and unconditional quantile regression of change in BMI distribution by IMD, age group and gender.

		Δ BMI 2009–2014						Δ BMI 2014–2019					
		OLS	Q50	Q75	Q90	Q95	Q99	OLS	Q50	Q75	Q90	Q95	Q99
IMD quintile	Least deprived	0.012	−0.225	0.383	0.238	0.635	0.554	0.171	0.096	0.126	0.250	0.451	4.591[b]
		(0.222)	(0.258)	(0.309)	(0.483)	(0.658)	(0.901)	(0.208)	(0.232)	(0.286)	(0.488)	(0.650)	(2.179)
	2nd	0.195	0.306	0.254	0.490	0.294	0.627	0.172	0.123	0.499	0.556	0.215	−0.474
		(0.226)	(0.263)	(0.329)	(0.550)	(0.718)	(1.538)	(0.218)	(0.240)	(0.334)	(0.499)	(0.543)	(1.828)
	3rd	0.640[b]	0.475[c]	0.843[b]	1.017[c]	1.509[c]	0.023	0.252	0.431	0.196	0.257	0.584	−1.695
		(0.257)	(0.285)	(0.375)	(0.567)	(0.886)	(3.373)	(0.252)	(0.273)	(0.338)	(0.566)	(0.883)	(1.510)
	4th	0.245	0.099	0.623	−0.308	0.201	2.301	0.190	0.463	0.146	0.258	−0.519	−1.091
		(0.283)	(0.314)	(0.425)	(0.623)	(0.933)	(1.672)	(0.256)	(0.311)	(0.376)	(0.515)	(0.868)	(2.215)
	Most deprived	0.008	−0.037	−0.041	−0.521	0.554	−3.997	1.295[a]	0.862[a]	1.768[a]	2.600[a]	3.069[a]	6.684[b]
		(0.321)	(0.390)	(0.446)	(0.704)	(0.901)	(3.009)	(0.270)	(0.321)	(0.424)	(0.646)	(0.736)	(2.688)
Age group	20–29	0.242	0.181	0.299	0.632	−0.814	1.620	0.778[b]	0.694[b]	0.914[b]	1.079	1.655	3.229[c]
		(0.319)	(0.335)	(0.474)	(0.912)	(1.202)	(2.595)	(0.323)	(0.329)	(0.453)	(0.978)	(1.504)	(1.797)
	30–39	0.200	0.234	0.620	0.810	0.383	1.025	0.775[a]	0.968[a]	1.141[a]	1.058	2.280[b]	2.016
		(0.262)	(0.303)	(0.382)	(0.646)	(1.032)	(2.012)	(0.257)	(0.318)	(0.376)	(0.643)	(0.948)	(2.179)
	40–49	0.318	−0.210	0.799[b]	0.889	0.556	−0.690	0.207	0.484[c]	0.206	−0.376	−0.357	0.328
		(0.257)	(0.294)	(0.393)	(0.694)	(0.883)	(2.063)	(0.242)	(0.273)	(0.386)	(0.564)	(0.793)	(1.877)
	50–59	−0.219	−0.107	0.005	−0.002	0.482	−1.819	0.280	0.062	0.415	0.545	0.311	2.936
		(0.283)	(0.341)	(0.418)	(0.614)	(1.031)	(2.003)	(0.237)	(0.292)	(0.635)	(0.521)	(0.835)	(2.177)
	60–69	0.543[b]	0.644[b]	0.693[c]	1.128[b]	1.161	0.585	0.034	0.007	0.569	0.617	0.316	−0.780
		(0.257)	(0.291)	(0.370)	(0.555)	(1.032)	(2.014)	(0.245)	(0.291)	(0.379)	(0.513)	(0.837)	(1.346)
	70–79	0.080	0.202	0.181	−0.133	−1.383	0.496	0.277	0.045	0.365	0.924[c]	1.185[c]	1.313
		0.300	(0.345)	(0.435)	(0.722)	(0.883)	(1.819)	(0.257)	(0.289)	(0.392)	(0.558)	(0.640)	(1.700)
	80+	0.051	0.355	0.393	−0.100	−0.251	−4.360	0.022	−0.086	−0.121	−0.344	0.760	−0.111
		(0.424)	(0.455)	(0.617)	(0.878)	(1.115)	(3.977)	(0.343)	(0.386)	(0.459)	(0.797)	(1.128)	(1.571)
Gender	Men	0.238	0.060	0.301	0.469	0.781	1.080	0.441[a]	0.370[b]	0.534[a]	1.100[a]	0.821[c]	0.224
		(0.160)	(0.174)	(0.213)	(0.325)	(0.514)	(1.175)	(0.150)	(0.160)	(0.205)	(0.325)	(0.484)	(1.533)
	Women	0.210	0.173	0.598[b]	−0.001	0.441	−0.652	0.370[b]	0.425[b]	0.486[b]	0.711[b]	0.976[c]	2.132[c]
		(0.173)	(0.199)	(0.266)	(0.412)	(0.570)	(1.097)	(0.156)	(0.186)	(0.238)	(0.352)	(0.515)	(1.138)

OLS=Ordinary Least Square regression, *Q*=quintile (unconditional quantile regression),.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

in England. Ten-year data from a representative sample of residents in England were analysed to estimate how those inequalities evolved over time and the role of key inequality drivers. Results indicated that groups living in the most deprived areas have both increased their average BMI score and proportion of obese individuals at an increasingly higher rate, relative to the rest of the population. Decomposition analyses indicated that having a limiting longstanding illness was the predictor consistently and most strongly associated with higher BMI, disproportionally contributing to severe obesity inequalities.

From a theoretical standpoint, this study contributes to the methodological development of analytical tools for monitoring population health outcomes and SDG targets at the local level. In addressing the limitations of currently available dashboards and traditional unidimensional approaches, the analytical framework presented here can be adapted to the monitoring of SDG targets beyond health inequalities. Indeed, future studies should focus on exploring its applicability to other public health goals such as quality education (SDG 4) or access to clear water and sanitation (SDG 6), where different socio-economic dimensions may be relevant to be monitored at the local level for policy decision making. This study also paves the way for more nuanced analyses and analytical tools for monitoring health inequalities, focusing on disease and risk profile severity and respective budgetary implications [48].

From a practical perspective, the integration of systems thinking into SDG policymaking is deemed essential for achieving coherent and effective outcomes, recognizing the interconnectedness of various goals and their broader implications for making progress towards sustainability [49]. In this vein, taking the empirical results presented in this paper, as base case they may be used by local governments to identify IMD areas and modifiable characteristics to design policies aimed to reduce excess weight and consequent longer-term health inequalities which is turn may lead to income inequalities reduction due to productivity improvements [50]. Another potential avenue would be that to target subgroups that lag behind in terms of multiple SDGs such as good health and wellbeing (3) and quality education (SDG 4) to target reduced inequalities (SDG 10), in an advocated approach of fostering collaboration and partnerships across public and economic sectors and levels of governance (SDG 17).

The key role that LGs and public health managers can play at the local level in achieving the SDG goals emphasises the need for a more systematic and granular approach to outcome monitoring and informing of policy decisions. In particular, it highlights the need to take active steps to planning for and ensuring that policy efforts spent towards addressing local level priorities feed into the achievement of SDG goals. In practice, however, it must be acknowledged that LGs face considerable challenges pertaining to data collection and analysis which could be coordinated at a central level. If evidence-based policy and budgetary decisions ought to be prioritised, then investment in research and analytical infrastructure and capacity need to be considered. These may not derive necessarily from structural investments, but rather from collaborations and partnerships established with universities and reputable research centres [51,52].

This study presented some limitations. The paucity of the data available, particularly on covariate information, limited the extent of statistical analysis for adequately addressing the potential confounding and therefore ensuring causality which is not implied. In addition, the IMD was selected as the socio-economic dimension of interest, which has been widely used by policy makers in England to inform public policy. However, other socio-economic dimensions along which excess weight inequalities have been shown to pattern, such as educational attainment [53], occupational status [54] and income level [55]. Moreover, and importantly, choice of socio-economic dimension, sub-population target and between absolute versus relative inequalities requires a value judgement which ultimately rests on elected officials with a mandate to such inequities. Marked heterogeneity in population demographics and socio-economic settings means that the issue of health inequities will take different forms and therefore priorities across management and decision-making contexts.

Conclusions

The achievement of SDG goals requires a societal effort where local governments can play a crucial role. To support these decision makers in supporting the UN 2030 Agenda, monitoring socio-economic inequalities and their determinants at the local level is important and can be pursued by applying an ECI and decomposition-based approach, as illustrated in this study. Such approach should be considered as a routine investigation by public health managers to inform SDG policy and budgetary decisions. Future research should apply the analytical approach presented here in different settings and test its usefulness and robustness to other health outcomes and determinants of inequality.

Statements and declarations

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Ethics approval

The data used in this study has been taken from publicly available surveys. No further ethics approval was therefore required for this study.

CRediT authorship contribution statement

Paolo Candio: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

No competing interests to disclose.

Data availability

The datasets analysed during the current study are available at https://digital.nhs.uk/data-and-information/publications/statistical/health-survey-for-england.

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Appendix A

Table A1
Sub-group trends in mean BMI change by IMD, age group and gender.

		BMI 2009		BMI 2014		BMI 2019		Δ BMI 2009–2014		Δ BMI 2014–2019	
		Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
IMD quintile	least deprived	ref	ref	0.012	0.222	0.182	0.237	0.012	0.222	0.171	0.207
	2nd	0.072	0.247	0.267	0.229	0.439[c]	0.239	0.195	0.226	0.172	0.218
	3rd	0.176	0.258	0.816[a]	0.248	1.068[a]	0.253	0.640[c]	0.257	0.252	0.252
	4th	0.370	0.280	0.615[b]	0.253	0.805[a]	0.252	0.245	0.283	0.190	0.256
	most deprived	0.474	0.321	0.482[c]	0.250	1.778[a]	0.270	0.008	0.321	1.295[a]	0.270
	Constant	27.014[a]	0.176	27.014[a]	0.176	27.014[a]	0.176	NA	NA	NA	NA
Age group	20–29	ref	ref	0.242	0.319	1.021[a]	0.343	0.242	0.319	0.778[b]	0.323
	30–39	1.467[a]	0.314	1.666[a]	0.292	2.441[a]	0.310	0.200	0.262	0.775[a]	0.257
	40–49	2.778[a]	0.312	3.096[a]	0.289	3.303[a]	0.300	0.318	0.257	0.207	0.242
	50–59	3.531[a]	0.332	3.311[a]	0.292	3.591[a]	0.293	−0.219	0.283	0.280	0.237
	60–69	3.052[a]	0.311	3.595[a]	0.290	3.629[a]	0.301	0.543[b]	0.257	0.034	0.245
	70–79	3.136[a]	0.341	3.216[a]	0.298	3.492[a]	0.304	0.080	0.300	0.277	0.257
	80+	2.094[a]	0.419	2.146[a]	0.344	2.167[a]	0.338	0.051	0.424	0.022	0.343
	Constant	25.040[a]	0.240	25.040[a]	0.240	25.040[a]	0.240	NA	NA	NA	NA
Gender	Men	ref	ref	0.238	0.160	0.679[a]	0.164	0.238	0.160	0.441[b]	0.149
	Women	−0.002	0.184	0.208	0.161	0.579[a]	0.168	0.210	0.173	0.370[c]	0.156
	Constant	27.232[a]	0.122	27.232[a]	0.122	27.232[a]	0.122	NA	NA	NA	NA

BMI= body mass index; IMD= Index of Multiple Deprivation;.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

Table B1
Factors contributing to excess weight across the BMI spectrum.

		OLS		Q50		Q75		Q90		Q95		Q99	
	$N = 16{,}508$	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
2009 by IMD quintile	2nd	−0.001	0.231	−0.220	0.300	0.230	0.375	0.086	0.553	0.379	0.814	1.817	1.823
	3rd	0.242	0.242	0.150	0.310	0.576	0.386	0.382	0.577	0.845	0.879	0.757	1.664
	4th	0.439	0.267	0.168	0.317	0.732[c]	0.392	1.761[a]	0.648	1.957[b]	0.969	4.371[c]	2.457
	most deprived	0.506[c]	0.302	0.390	0.338	1.222[a]	0.440	1.747[b]	0.707	1.716	1.057	3.523	2.606
2014 by IMD quintile	least deprived	0.134	0.208	−0.175	0.270	0.449	0.337	0.702	0.495	0.700	0.704	1.517	1.483
	2nd	0.334	0.216	0.022	0.275	0.604[c]	0.345	1.144[b]	0.531	0.893	0.749	2.284	1.673
	3rd	0.828[a]	0.233	0.585[b]	0.282	1.395[a]	0.360	1.643[a]	0.561	2.696[a]	0.873	3.568[c]	1.829
	4th	0.840[a]	0.240	0.436	0.286	1.419[a]	0.361	2.302[a]	0.580	2.421[a]	0.857	3.778[c]	2.045
	most deprived	0.625[a]	0.242	0.506[c]	0.297	1.435[a]	0.372	1.616[a]	0.579	2.350[a]	0.907	0.685	1.635
2019 by IMD quintile	least deprived	0.290	0.228	−0.049	0.278	0.589[c]	0.352	1.178[b]	0.547	1.761[b]	0.810	3.937[c]	2.042
	2nd	0.599[a]	0.227	0.254	0.282	1.317[a]	0.358	1.680[a]	0.541	1.286[c]	0.758	2.271	1.612
	3rd	1.209[a]	0.239	1.125[a]	0.288	1.799[a]	0.365	2.459[a]	0.579	3.035[a]	0.877	1.968	1.683
	4th	1.091[a]	0.242	0.986[a]	0.296	1.738[a]	0.371	2.149[a]	0.592	2.040[b]	0.870	2.878	1.801
	most deprived	1.687[a]	0.264	0.958[a]	0.291	2.424[a]	0.389	4.575[a]	0.664	5.856[a]	1.036	7.259[a]	2.318
Age group	30–39	1.330[a]	0.173	1.587[a]	0.190	1.354[a]	0.220	0.608[c]	0.364	0.836	0.572	0.741	1.363
	40–49	2.229[a]	0.174	2.398[a]	0.187	2.233[a]	0.231	1.456[a]	0.392	1.165[c]	0.612	1.210	1.461
	50–59	2.431[a]	0.178	2.752[a]	0.192	2.621[a]	0.245	1.305[a]	0.415	0.439	0.635	0.788	1.569
	60–69	2.140[a]	0.184	2.661[a]	0.196	2.089[a]	0.250	0.945[b]	0.429	−0.256	0.660	−2.183	1.554
	70–79	1.693[a]	0.201	2.542[a]	0.218	1.540[a]	0.282	−0.254	0.475	−2.459[a]	0.721	−5.877[a]	1.567
	80+	0.412[c]	0.235	1.363[a]	0.278	−0.323	0.341	−2.968[a]	0.524	−5.251[a]	0.785	−6.799[a]	2.027
Gender	Women	−0.178[b]	0.090	−0.665[a]	0.101	0.342[a]	0.132	1.656[a]	0.215	2.473[a]	0.325	3.688[a]	0.780
Region	North West	−0.439[b]	0.206	−0.558[b]	0.231	−0.512	0.320	−0.220	0.514	−0.335	0.753	−0.342	1.847
	Yorkshire & Humber	−0.462[b]	0.217	−0.711[a]	0.245	−0.483	0.335	−0.456	0.533	0.011	0.797	−1.529	1.871
	East Midlands	−0.185	0.218	−0.230	0.250	0.039	0.344	0.028	0.551	0.439	0.811	−2.080	1.821
	West Midlands	0.025	0.223	−0.187	0.245	0.236	0.347	0.756	0.574	1.282	0.875	−1.476	1.847
	East of England	−0.445[b]	0.203	−0.507[b]	0.240	−0.550[c]	0.325	−0.333	0.514	−0.568	0.739	−1.104	1.738
	London	−1.149[a]	0.214	−1.429[a]	0.247	−1.374[a]	0.321	−0.860[c]	0.511	−0.437	0.769	−1.276	1.832
	South East	−0.687[a]	0.199	−0.796[a]	0.228	−0.808[a]	0.309	−0.519	0.492	0.271	0.733	0.333	1.747
	South West	−0.178	0.215	−0.173	0.245	0.053	0.339	0.226	0.545	0.370	0.787	−2.993[c]	1.646
Ethnicity	Mixed	0.329	0.408	0.512	0.498	−0.191	0.526	−0.758	0.803	1.516	1.528	0.191	3.195
	Asian	−0.827[a]	0.180	−0.427[b]	0.210	−1.007[a]	0.248	−2.105[a]	0.375	−2.799[a]	0.534	−2.161	1.367
	Black	1.349[a]	0.310	1.680[a]	0.345	1.533[a]	0.485	1.128	0.797	1.585	1.282	−0.154	3.324
	Other	0.158	0.450	0.095	0.555	−0.328	0.692	−0.188	1.146	−0.223	1.755	−3.640[c]	2.209
Limiting LI	Non-limiting LI	−0.354[b]	0.151	−0.162	0.154	−0.726[a]	0.220	−1.740[a]	0.383	−1.733[a]	0.595	−2.525[c]	1.507
	LI	−1.530[a]	0.127	−1.231[a]	0.128	−2.058[a]	0.179	−3.597[a]	0.312	−4.651[a]	0.480	−7.083[a]	1.208
Education	Higher ed below degree	0.778[a]	0.152	0.893[a]	0.182	0.923[a]	0.239	0.677[c]	0.371	0.678	0.531	0.270	1.225

(*continued on next page*)

Table B1 (*continued*)

N = 16,508	OLS Mean	OLS SE	Q50 Mean	Q50 SE	Q75 Mean	Q75 SE	Q90 Mean	Q90 SE	Q95 Mean	Q95 SE	Q99 Mean	Q99 SE
NVQ3/GCE A Level equiv	0.904[a]	0.145	0.979[a]	0.169	1.203[a]	0.216	1.066[a]	0.338	1.555[a]	0.509	1.354	1.307
NVQ2/GCE O Level equiv	1.133[a]	0.140	1.174[a]	0.155	1.317[a]	0.205	1.944[a]	0.338	2.116[a]	0.514	1.912	1.273
NVQ1/CSE other grade equiv	0.910[a]	0.249	1.012[a]	0.271	1.396[a]	0.373	1.482[b]	0.621	2.612[a]	0.965	0.323	1.735
Other	0.529	0.355	0.428	0.423	0.894	0.586	0.490	0.941	0.859	1.351	−0.951	2.432
No qualification	1.172[a]	0.150	1.216[a]	0.166	1.314[a]	0.218	1.555[a]	0.359	2.817[a]	0.568	3.206[b]	1.384
Full-time student	−0.628[b]	0.294	−0.492	0.323	−0.011	0.359	0.111	0.620	−1.094	0.726	−1.316	1.664
Constant	26.224[a]	0.303	25.407[a]	0.357	28.543[a]	0.458	33.411[a]	0.728	36.363[a]	1.117	45.839[a]	2.280
R-squared	0.085		0.075		0.054		0.038		0.029		0.010	

LI= longstanding illness; Region of reference: North East, Q=quantile; SE=standard error;.

[a] $p < 0.01$.

[b] $p < 0.05$.

[c] $p < 0.1$.

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