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What We Know, Think We Know, or Are Starting to Know

In the public health conversation, there is one word you may consistently hear: *policy*. But what meaning does this word hold? Broadly, 'policy' may be defined as a framework or set of rules to guide decisions and outcomes.

Thus defined, a policy is not binding law; to become law in the United Kingdom requires that the policy is proposed in legislation and enshrined in a relevant Act of Parliament [i.e., it has been approved by the government].

And here is where we reach perhaps the most important battleground for public health nutrition. To enact policy as statutory law requires the government to have the political will to step in. For public health nutrition, the evidence is now unequivocal that the major issue is the deliberate fostering of a food environment that promotes poor diets and ill-health⁽¹⁾.

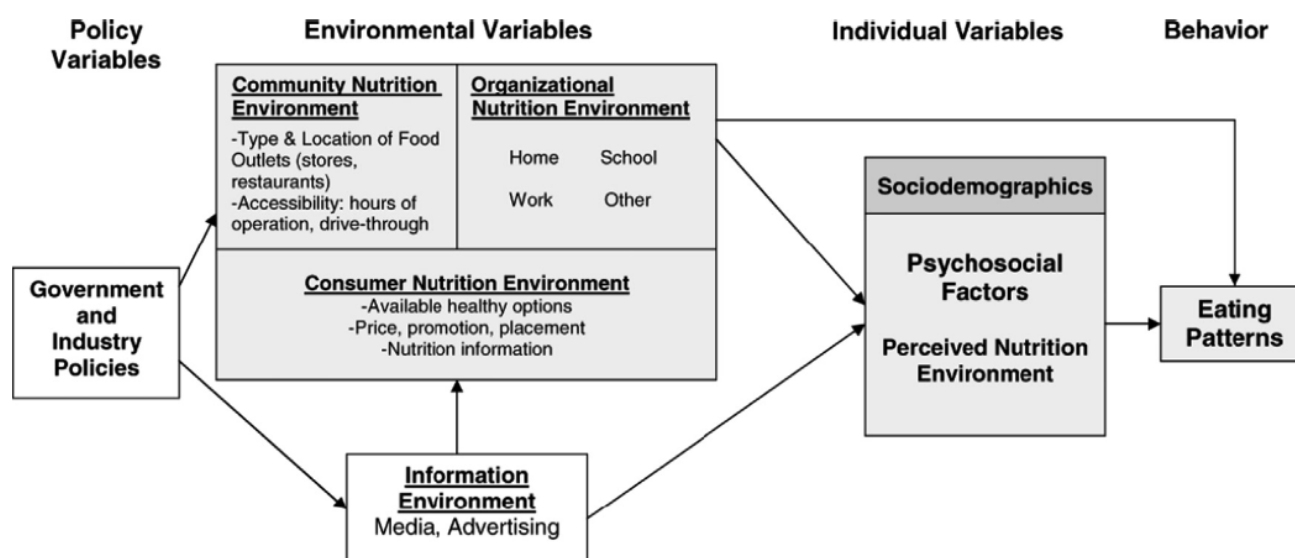


Figure from ⁽²⁾ illustrating factors that influence the food and nutrition environment.

However, the prevailing political and economic model in certain developed countries, of which the UK is one, is predicated on government not intervening in the private sector through legislation or regulation, and instead emphasising the social responsibility of the individual to navigate the environment ⁽³⁾.

To maintain that this position is tenable requires evidence that the food industry and its ancillaries, e.g., advertising and marketing, would exhibit corporate responsibility

and voluntarily mitigate against commercial determinants of health ^(4,5). In fact, the available evidence in the UK from voluntary, opt-in policy schemes shows that these policies are doomed to failure; the food industry made little effort to reduce the calorie content, or improve the healthfulness, of foods ⁽⁶⁾.

Then, finally, public health nutrition in the UK eked out a hard-fought win. In 2016 a new policy was announced; the Soft Drinks Industry Levy [SDIL], a tax on the food industry for sugar-sweetened beverages that was enacted in section 36A of the Finance Act 2017. So, has the “sugar tax” been successful?

The Study

The study analysed trends in childhood overweight/obesity rates over the period from before to after the introduction of the SDIL, using a method of analysis known as an “interrupted time-series analysis”* [see ***Geek Box** below for further details].

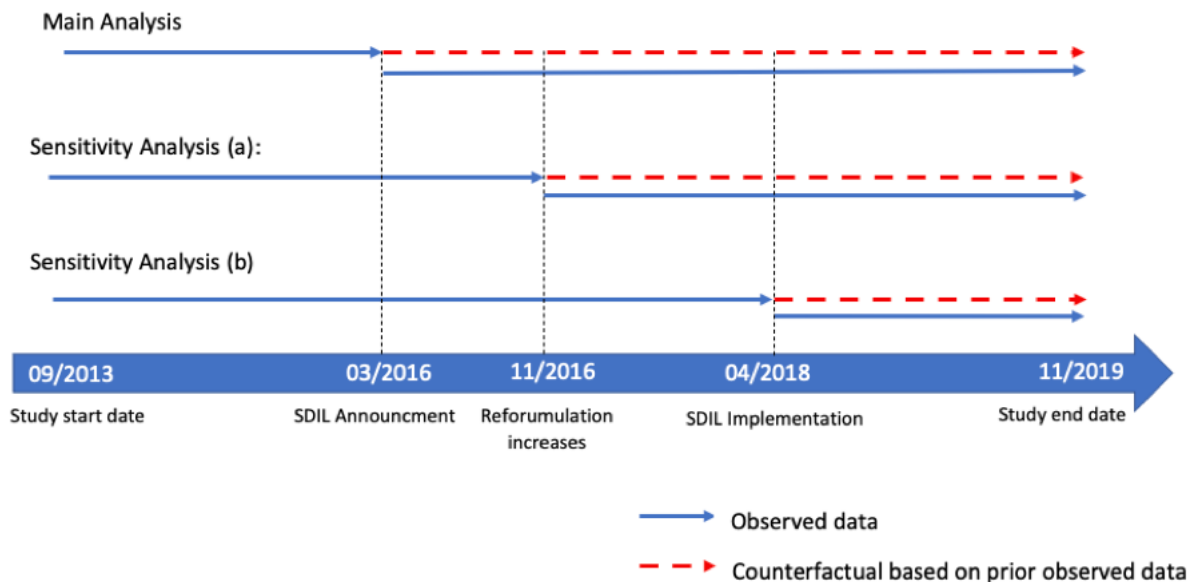
Data on children’s weights was derived from the National Child Measurement Programme [NCMP], which collects annual data on height and weight in ~1-million UK schoolchildren aged 4–5yrs and 10–11yrs, respectively.

The analysis was based on a counterfactual, an epidemiological research method which compares a factual outcome [i.e., the implementation of the SDIL] against an outcome that is assumed would have been observed but for the factual outcome, but did not in fact occur [i.e., is ‘counter to the factual outcome’, in this case that the SDIL was not implemented]. Thus, the analysis in the present study compared two scenarios:

- **Factual:** Observed data trends in childhood overweight/obesity before and after announcement and implementation of the SDIL.
- **Counterfactual:** Estimated trends in childhood overweight/obesity had the SDIL *not* been announced and implemented, based on the pre-announcement/implementation data trends.

The entire time-series of the study covered trends in childhood overweight/obesity from September 2013 to November 2019. The study analysis used three specific time-series interruption dates to create the counterfactual scenarios [see **figure** below for an illustration of each analysis]:

- **Primary Analysis:** Counterfactual comparing childhood overweight/obesity trends before and after a time-series interruption date of March 2016, corresponding to the announcement of the SDIL.
- **Sensitivity Analysis A:** Counterfactual comparing childhood overweight/obesity trends before and after a time-series interruption date of November 2016, corresponding to the beginning of industry reformulation of sugar-sweetened beverages [SSB].
- **Sensitivity Analysis B:** Counterfactual comparing childhood overweight/obesity trends before and after a time-series interruption date of April 2018, corresponding to the statutory implementation of the SDIL.



*Geek Box: Interrupted Time-Series Analysis

Interrupted time series [ITS] analysis is a method used in epidemiology to evaluate the effect of population-wide public health interventions. Breaking down the name may help to understand what this analysis is evaluating. Imagine there is a public health policy that came into place in January 2022; this policy is the ‘intervention’ from the previous status quo. And let’s say we were interested in the effect of the intervention 1-year later; we could establish a ‘time series’ of 1-year prior to the intervention and 1-year post intervention.

It is important to note that this type of analysis is not looking at individual-level effects and averages [i.e., means] calculated from individual-level effects, as would be done in a randomised controlled trial [e.g., measuring every participant’s cholesterol levels] or prospective cohort study [e.g., assessing every participant’s diet with a food-frequency questionnaire]. Rather, ITS is specifically looking at population-level effects, e.g., does the introduction of a vaccine reduce prevalence and incidence of a disease in the population compared to before.

While this is a strength of ITS, it also opens the limitations of this analytical approach unless other methods are considered in the analysis. A good ITS analysis compares a population who received an intervention to a population that did not receive it, which can be the same population compared before and after an intervention was introduced.

This allows for the framing of a “counterfactual” scenario, which describes the effect of an exposure on an outcome contrasting two potential outcomes. For example, the effect of a vaccine on a disease can be contrasted between those who received the vaccine and those who did not; it is not possible for someone to have had both outcomes. In effect, the counterfactual scenario estimates what would have happened in the absence of the intervention.

This allows for effective use of ITS analysis to compare trends in the exposure-outcome relationship of interest in the group exposed to the intervention compared to the counterfactual situation.

Results: Irrespective of sex and age of included schoolchildren, the highest prevalence of obesity was observed in areas with the highest social deprivation level. Prevalence of obesity was higher in Year 6 pupils [10–11yo] compared to Reception class [4–5yo].

Primary Analysis Year 6 [10–11yo]: Compared to the counterfactual scenario of no SDIL announcement or implementation, there was a relative reduction of obesity prevalence in overall 10–11yo schoolchildren of 3.6% [95% CI, 1.2% to 5.9%], corresponding to an absolute reduction of 0.8% [95% CI, 0.3% to 1.3%].

This effect was greatest in children from the most socially deprived areas; a relative reduction of 4.1% [95% CI, 1.8% to 6.3%] in the most socially deprived areas, and 5.5% [95% CI, 3.3% to 7.7%] in the second-most socially deprived areas.

Sex differences were also noted, and the reduction in obesity prevalence was only significant in 10–11yo girls, but not boys. In girls, there was a relative reduction of obesity prevalence of 8.0% [95% CI, 5.4% to 10.5%]. The greatest reduction was also observed in girls from the two lowest quintiles of social deprivation. Conversely, 10–11yo boys in the least deprived areas showed a significant increased obesity prevalence of 10.1% [95% CI, 4.3% to 15.9%].

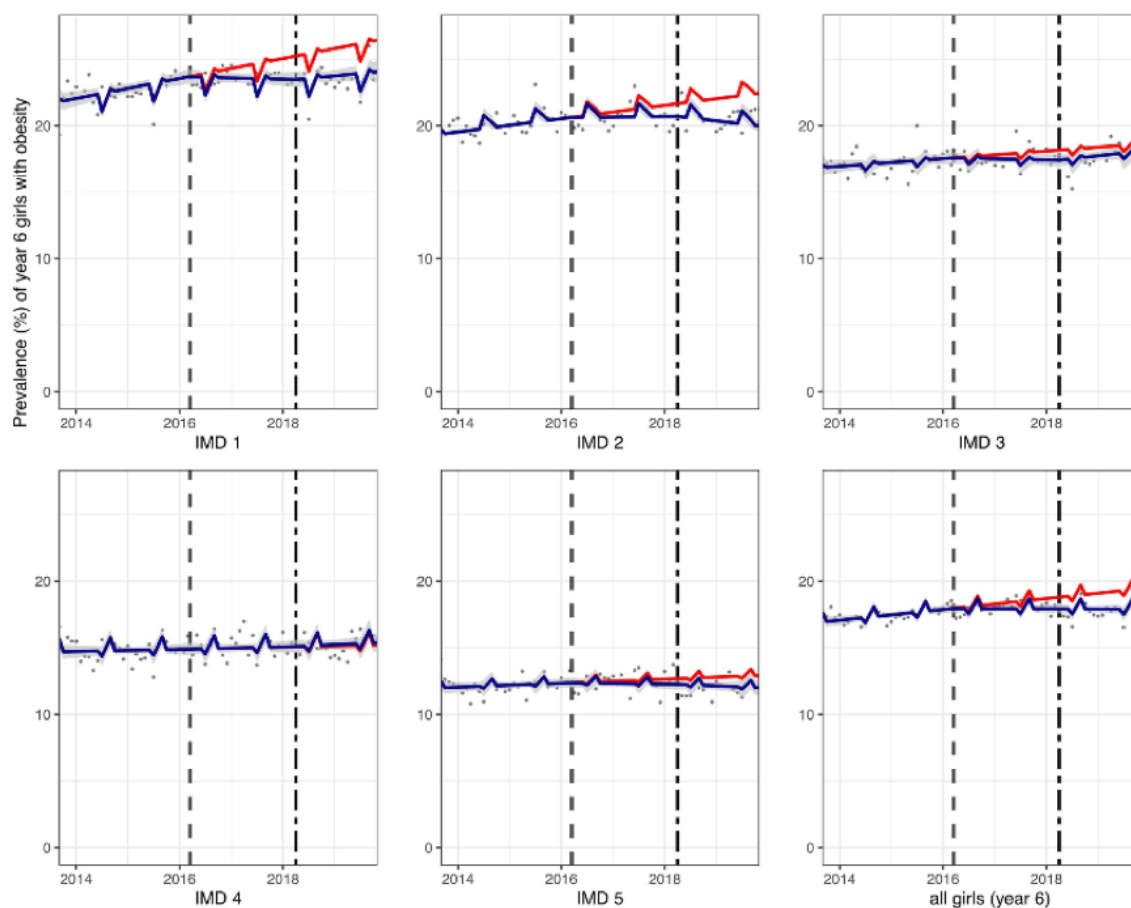


Figure from the paper illustrating the change in obesity prevalence in girls. “IMD” = Index of Multiple Deprivation, which is a composite score of social deprivation including data on income, employment, education, housing, health, crime, and living environment. IMD 1 = areas of greatest social deprivation; IMD 5 = areas of least social deprivation. As you can see if you look at IMD 1 and 2 **[top right and top middle, respectively]**, trends in obesity in 10 – 11yo girls started to diverge from the counterfactual trend scenario **[red line]** after between announcement [2016] and implementation [2018] of the SDIL.

Primary Analysis Reception [4–5yo]: Compared to the counterfactual scenario of no SDIL announcement or implementation, there was no significant reduction of obesity prevalence in overall 4–5yo schoolchildren.

However, analysis by social deprivation level indicated that prevalence of obesity increased by 10% [95% CI, 2.2% to 17.9%], compared to the counterfactual, in 4–5yo schoolchildren from the least deprived areas.

This observation was significant in both boys with an increased obesity prevalence of 9.7% [95% CI, 2.0% to 17.4%] from the least deprived areas, as well as girls from the least deprived areas with an increased obesity prevalence of 10.8% [95% CI, 0.1% to 21.5%].

Sensitivity Analyses: In the first sensitivity analysis, which considered the interruption point as the date at which reformulation began in November 2016, the results were consistent with the findings of the primary analysis outlined above.

In the second sensitivity analysis, which considered the interruption point as the date at which the policy was implemented as statutory law in April 2018, however, significant reductions in obesity prevalence in either overall 4–5yo or 10–11yo boys or girls were no longer observed. In fact, this sensitivity analysis indicated that obesity prevalence in 4–5yo schoolchildren increased by 7.1% [95% CI, 0.8% to 13.4%], which was similar in terms of relative increase in both boys and girls.

The Critical Breakdown

Pros: The study was preregistered, and the study protocol was published in advance of the analysis. The NCMP programme is a comprehensive national programme that is highly powered with ~1-million participating children, and participation rates of >90% of eligible schoolchildren. The analysis specifically factored in social deprivation index, to determine whether the impact of the “sugar tax” varied by social deprivation level [more under **Key Characteristic** and **Interesting Finding**, below]. Further, because the announcement of the SDIL, the beginning of industry reformulation of SSB, and the statutory date of implementation of the SDIL, differed across the period of the analysis, the study conducted distinct time-series interruption analyses based on each relevant respective date.

Cons: The SDIL was legally implemented in April 2018 and the follow-up period of the study was curtailed due to the UK leaving the European Union [December 2019] and the subsequent national Covid-19 lockdown [March 2020]. Thus, the data for the sensitivity analysis from the implementation date is very short-term, and the divergent findings may be a ‘false positive’ due to the lack of adequate data for a more robust counterfactual comparison. Conversely, as the authors note, it could be that the reformulation of SSB had already largely occurred, such that observed changes in prevalence of obesity were no longer evident. The analysis is based on national level data, and it is not possible to distinguish whether the effects of the SDIL may be greater in, for example, urban compared to rural regions.

Key Characteristic

The key characteristic of the present study is the specific stratification of the analysis according to quintiles [fifths] of social deprivation. This is crucial in any analysis of public health nutrition policy, given that exposure to unhealthy food advertising in children may be greater in children from lower socio-economic status ⁽⁷⁾.

And we have evidence that children are responsiveness to unhealthy food advertising, with an increased likelihood of choosing unhealthy foods and beverages in response to marketing of such foods and beverages ⁽⁸⁾.

Given the evidence that, a) children are responsive to unhealthy food marketing, and b) children from lower socio-economic status areas have greater exposure to unhealthy food marketing, the combination of these factors is why public health policy focused on individual behaviour change disproportionately disadvantages those from less advantaged backgrounds ⁽⁹⁾.

This latter point is important because one of the main hesitations for the “sugar tax” was that it would disproportionately financially impact the most disadvantaged in society ⁽¹⁰⁾. And this leads us to the interesting finding of the present study...

Interesting Finding

As noted above, there were fears that introducing a “sugar tax” had potential for such a levy to disproportionately affect more socially disadvantaged population groups ⁽¹⁰⁾. However, this was in fact addressed in the terms of the SDIL policy itself, which was a tax on *industry*, not one passed on to the individual consumer through higher product prices [which has been the approach in Mexico and the United States].

Given that the financial implications of the “sugar tax” were not passed on to consumers, the next relevant question was whether a broad, population-based approach would result in meaningful differences in higher risk populations, which for obesity risk corresponds to more socially deprived population groups ⁽⁹⁾.

The data from the present study clearly showed that the greatest overall difference in obesity prevalence was observed in children from the lowest two quintiles of social deprivation. This is important data, providing evidence that the benefits of whole-population “upstream” public health interventions reach, and positively impact, vulnerable population groups.

Relevance

The evidence accumulating in relation to the SDIL in the UK continues to highlight the positive impact of this legislation. The SDIL levied a charge of £0.18 [pence] per litre on SSB containing between 5g to 8g sugar per 100ml, and £0.24p/L on drinks containing >8g/100ml. The food industry could avoid such taxes altogether if their product contained less than 5g/100ml.

The fact that the food industry had two years prior to the SDIL being statutorily implemented in April 2018 provided a grace period for industry to begin to reformulate products. This has been overwhelmingly successful, with the percentage of drinks on

the market with >5g/100ml sugar fell from 49% to 15% between September 2015 and February 2019 ⁽¹¹⁾.

The present analysis adds to this literature by indicating that in children, particularly older children of 10–11yrs, the announcement of the tax and the period of reformulation were associated with declining relative and absolute prevalence rates of obesity.

This evidence sits within a long-standing debate within public health as to whether whole-population or subgroup-targeted strategies are more efficacious ^(9,12). The merits of a population-based approach or targeted strategy depend on the influence of specific risk factors, which differ by disease. For obesity and related cardio-metabolic risk, we know that risk factors include socio-economic status, ethnicity, urbanisation, food access and nutrition quality ⁽⁹⁾. This underlies the rationale for a population-based approach, in that many factors driving obesity are behavioural and/or environmental in nature, and thus beyond the control of the individual.

Application to Practice

It is important to note that a counterfactual epidemiological analysis, while attempting to mimic a controlled intervention, remains an associative study and the observed changes may not entirely reflect the SDIL in isolation.

And the lack of reduction in obesity observed in the sensitivity analysis with the interruption date of April 2018 [the date of statutory implementation] may mean that the effect of the policy had plateaued.

Nevertheless, the evidence for the impacts of the SDIL, both in terms of reformulated SSB ⁽¹¹⁾, and the present study indicating a reduction in childhood obesity prevalence, suggest that upside to encroachments on the economic freedom of the food industry outweigh the cost of inaction.

Given that the policy of restricting high fat/sugar/salt [HFSS] food advertising on the Transport for London network also resulted in significant reductions in calories purchased from HFSS foods [we [covered this study in a previous Deepdive](#)], the evidence is now accumulating in favour of “upstream” interventions to make meaningful differences in the food environment, intake, and diet-related health risks.

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