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ORIGINAL ARTICLE

Oral health, sugary drink consumption and the soft drink industry levy: Using spatial microsimulation to understand tooth decay

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Abstract

Spatial microsimulation is a powerful tool for creating large-scale population datasets that can be used to assess spatial phenomena in health-related outcomes. Despite this, it remains underutilized within dental public health. This paper outlines the development of an oral health focused micro-simulation model for Sheffield (UK, SimSheffield), and how this can be used to assess potential socio-spatial impacts of a sugar tax which was introduced in the United Kingdom in 2016 and is known as the Soft Drink Industry Levy (SDIL). Exploratory analysis showed areas paying more SDIL were not those with the highest tooth decay or deprivation scores as might be hoped (in the first case) and expected from the literature (in the second).

KEYWORDS
geography, oral health, policy, spatial microsimulation, sugar tax

JEL CLASSIFICATION
C31, C63, I14, I18, I38, R23, H79

1 | INTRODUCTION

Geographical approaches to health-related outcomes and inequalities are of great importance and allow for better understanding of the patterning of disease (Broomhead et al., 2019). It is also important to consider the socio-spatial justice aspect of policies affecting health in different locations, where inconsistent models for policy-making have been found (Cairney et al., 2022), as well as the benefits that health-related policies can have for societies and economies long term (Alwago, 2022). Despite the acknowledged importance of geography and regional science approaches in other health fields, there have been relatively few attempts to add spatial dimensions to work in the field of oral health. Of the existing examples, many have used these to demonstrate spatial variation in outcomes such as dental trauma (Carvalho et al., 2010) and caries (tooth decay, Antunes et al., 2002), while other studies have used geographical perspectives to investigate access to services (Kruger et al., 2011; McKernan et al., 2016) and workforce numbers (Feng et al., 2017). Additionally, there have been efforts to provide evidence-based analysis of future problems facing dentistry in relation to staffing issues (Jager et al., 2016) and new locations for dental surgeries (Horner & Mascarenhas, 2007). Despite this body of work, there has been a lack of oral health-related studies incorporating geographical perspectives in analysing policy-related outcomes.

One method traditionally used to aid with spatial analysis is spatial microsimulation. This method provides a mechanism to produce statistically sound synthetic local populations with specific attributes and then interpolate policy outcomes for their local areas using statistical models. Microsimulation was first conceptualized and developed in the field of economics (Orcutt, 1957) and has been used extensively for analysing effects of population change on government policies (and vice versa), with spatial elements added by geographers in the 1970s (with the first relevant conceptual framework developed by Wilson and Pownall, 1976) and 1980s (with the first application presented by Clarke et al., 1984). Since then there has been a growing number of relevant studies and applications (for comprehensive reviews see Ballas & Clarke, 2009; Tanton, 2014; Ballas et al., 2019; and for a recent review of public-health-related studies see Smith, Heppenstall, & Campbell, 2021).

Spatial microsimulation is a method that has been added to the tools that regional scientists have long established and used to address limitations, and have a history of taking geographical approaches to model small area data and 'what-if' scenarios related to health, social policy and welfare. This toolkit includes efforts to estimate small area distributions of health-related variables, such as the work of Congdon (2020) employing a Bayesian estimation method strategy (with Markov chain Monte Carlo techniques) to estimate a diabetes risk index for small areas in England, and the work of Moon et al. (2007) who used a multilevel synthetic estimation model to construct an age-sex-ethnicity disaggregated geography of obesity, also in England.

There has also been a rapidly growing number of studies aimed at developing and applying spatial microsimulation models for the estimation and analysis of health-related variables and policies. These include studies about the effects of tax rate changes and housing benefits in the Lothian region of Scotland (Campbell & Ballas, 2013), effects of locations of stop smoking services in Leeds, UK (Tomintz et al., 2008), and rates of anxiety, depression, long-term illness and drug and alcohol problems in York, UK (Ballas et al., 2006). These examples utilized spatial microsimulation to estimate potential impacts on populations using various 'what-if' scenarios. Other health-related examples of using spatial microsimulation to create 'new' variables include the work of James et al. (2019), who provide estimates of 106 product categories of food, drink and tobacco expenditure at the local (local authority district) level in Great Britain and studies investigating obesogenic environments (Edwards et al., 2010; Edwards & Clarke, 2009).

The latter studies demonstrated links between social capital and deprivation in patterns of childhood obesity (Edwards & Clarke, 2009), and that key covariates of obesity differed depending on an area's deprivation profile (Edwards et al., 2010). More recent work with the same theme includes a study by Koh et al. (2018) who present an analysis of adult obesity prevalence at the county level in the United States. Further examples of health-related applications of spatial microsimulation include analysis of depression rates in the Republic of Ireland (Morrissey et al., 2010), small area estimates of angina and diabetes (Burden & Steel, 2016), and dietary patterns and obesity in Brazil (Cataife, 2014).

Static spatial microsimulation (sometimes referred to as 'microsynthesis' or synthetic reconstruction) creates simulated population microdatasets at small area levels (Ballas et al., 2006; Whitworth et al., 2017) by combining local population counts of people with known attributes (usually from census data) with national level microdata (usually representative surveys of anonymized individuals) to generate a simulated local-area population that not only contains a statistically sound geographical distribution of the originally known attributes, but also 'new' attributes drawn from the microdata that are found in association with the original attributes. This approach stems from a general lack of publicly available geographically specific (small area) individual-level microdata, including in oral health research. The method creates one dataset containing all variables of interest (Broomhead et al., 2019), for small geographical areas for which small area microdata is either non-existent or usually restricted. Where some datasets are available, such as the Sample of Anonymised Records (Office for National Statistics, 2011a), they are often restricted to small samples, and not available for small area geographies, due to cost and confidentiality issues. National-level surveys, while a form of microdata, are often only available at broad regional levels. Spatial microsimulation therefore allows for the potential to estimate at the small area level and map outcome variables of interest with a variety of socio-economic and demographic indicators, allowing researchers to 'paint a picture of the possible (or most probable) life of households of a city or region' (Ballas et al., 2005).

Nevertheless, among the drawbacks of spatial microsimulation is the difficulty in estimating the extent of uncertainty in the small area estimates and of the reliability of the outputs (Tanton et al., 2014). However, there has been considerable progress in addressing this issue, following the work of Whitworth et al. (2017) who presented a method for estimating uncertainty in spatial microsimulation, which was also applied in a recent study of diet outcomes in England (Smith, Vogel, et al., 2021).

There are currently no spatial microsimulation studies within dental public health. Brown et al. (1995) used microsimulation to assess effects of insurance and fee changes on oral health outcomes in the United States, however, this research was conducted at the national level, with no small area analysis. This reflects the lack of small area analyses within the dental public health literature. Spatial microsimulation has considerable potential for the field, given its ability to combine data sources to create unique individual-level datasets and assess spatial patterns of health in more detailed ways. The aim of this study is to demonstrate this potential and its relevance to regional science policy and practice. We present a prototype spatial microsimulation model to produce a representative population of individuals with dental-related characteristics at the small area level, and to demonstrate potential uses of such a powerful modelling technique. The model is developed for Sheffield (UK), but the base method can be adapted for application in any city or region if similar suitable input datasets are available. To the best of our knowledge, this is the first application of spatial microsimulation within oral health research related to small area health outcomes and relevant oral health policies.

This paper outlines the development of the SimSheffield model, created to provide a better source of oral health and sociodemographic data for the city, and demonstrates how the model can be used to assess potential social and spatial impacts of relevant national policies. This research is timely given the introduction of the Soft Drink Industry Levy (HM Revenue and Customs, 2016) which has direct consequences for oral health. Section 2 outlines potential uses for the data, including a brief outline of the UK policy context surrounding the Soft Drink Industry Levy (referred to as SDIL in the remainder of the paper), and social implications of the tax. Section 3 summarizes the methods used to create and validate the model. Section 4 discusses the model in relation to relevant policies and spatial implications, and Section 5 discusses the overall model. Finally, Section 6 offers concluding comments.

2 | THE UK POLICY CONTEXT—THE SOFT DRINK INDUSTRY LEVY

Over the past decade there have been important relevant policy debates regarding the need to have clear information and guidelines regarding what should be considered a healthy diet, as well as the need for relevant recommendations. In this context, the UK Scientific Advisory Committee on Nutrition published a report on what the appropriate level of dietary carbohydrates for a healthy diet should be and made specific recommendations regarding the levels of free sugars and fibre intakes for the mean population (Scientific Advisory Committee on Nutrition, 2015). There have also been concerns about the social justice dimension relating to the costs of healthy diets; for example, Scarborough et al. (2016) modelled the dietary and cost implications of incorporating new sugar and fibre government guidelines.

These policy and scientific debates are also very relevant to the adoption of the SDIL which we briefly referred to in the introductory section. In particular, the SDIL, introduced on 6 April 2018 by the UK Government, applied to soft drinks with added sugar. The levy has two 'rates', one for drinks with sugar content of 5 g or more per 100 mL, and a higher rate for drinks containing 8 g of sugar or more per 100 mL (HM Revenue and Customs, 2016). Soft drinks containing 8 g of sugar or more are subject to a tax rate equivalent to 24 pence per litre, while soft drinks containing 5–8 g of sugar are subject to a tax rate equivalent to 18 pence per litre. Pure fruit juices (containing no added sugar) and drinks with a high milk (calcium) content are exempt. The policy was designed to combat obesity by encouraging producers to either reformulate products or reduce portion sizes for drinks with added sugar to avoid the levy. There have been arguments about the efficacy of the SDIL, with some research finding that the policy may be having positive effects already in reducing exposure to sugar sweetened beverages (SSBs, Scarborough et al., 2020). While the policy has been generally supported among parents and other adults (Gillison et al., 2020; Pell et al., 2019), some commentators have emphasized individual responsibility for health, and the unfairness of taxes (Bridge et al., 2020).

As is the case with the wider theme of healthy diet adoption and affordability, it is also important to consider the implications of the SDIL implementation from a social and socio-spatial justice perspective. Evidence suggests that higher sugar consumption from soft drinks, linked to higher levels of tooth decay, is more prevalent among those on lower incomes (Burt et al., 2006) and from lower socio-economic backgrounds (Warren et al., 2009). Additionally, these groups are often served by fewer large chain supermarkets, which offer wider varieties of produce (Fonseca, 2012) and are more likely to be near stores 'offering high-energy, low-nutrient-dense foods' (Mobley et al., 2009). High prices for healthier produce and travel distances to these represent further barriers, and a double burden (Fonseca, 2012). Public health policies can also have unintended consequences. International examples demonstrate that while taxation can reduce levels of SSB consumption, this is sometimes due to reductions being concentrated in higher socio-economic groups, widening inequalities (Riediger & Bombak, 2018).

There are assumptions that due to higher consumption, groups from lower socio-economic backgrounds would experience greater benefits from SSB taxes (Powell & Chaloupka, 2009; Puhl & Heuer, 2010). In line with this, a systematic review found consistent evidence that taxes on SSBs were associated with reductions in SSB consumption and improvements in population health (particularly obesity), with these benefits being either of a similar magnitude across social groups, or to a greater extent in lower versus higher socio-economic groups (Backholer et al., 2016). However, research has also shown these policies can be financially regressive, with low-income groups paying the largest proportion of income in tax (Kao et al., 2020), although the monetary burden across all household groups has been described as small (Backholer et al., 2016).

Taxations can also have stigmas attached. It is often assumed that individuals will give up products through personal responsibility once policies are enacted (Riediger & Bombak, 2018), and can be looked upon negatively through unhelpful and stigmatizing stereotypes (laziness, lack of willpower) when this does not happen (Puhl & Heuer, 2010). This has previously been demonstrated in relation to smoking cessation in low-income groups (Hoek & Smith, 2016). Given that the objective of the SDIL is to reduce obesity, there may be a risk of further stigmatizing individuals with low income or obesity. However, changing family diets can be challenging due to financial pressures and lack of support (Barker et al., 2008). It has also been noted that beverages not usually included in these taxes, such as sweetened coffee and tea, are usually associated with higher socio-economic status. This potentially leads to situations where more economically advantaged groups, who are likely to have more income and choice in consumption, are still able to consume their untaxed sweetened beverages, while disadvantaged groups are taxed on the sugary and soft drinks they consume, despite often having similar sugar content (Riediger & Bombak, 2018).

It is therefore important to consider effects of such policies beyond the immediate goals of reducing SSB consumption and obesity. Spatial microsimulation can contribute to this debate, and the evidence base on potential social, economic and geographical impacts of the levy, by demonstrating the spatial distribution of individuals who (and where) may be most affected. It is now accepted beyond doubt that higher SSB consumption is associated with more decayed teeth (Sheiham, 2001), with the low pH and highly titratable acidity of some drinks causing erosion of enamel, while the metabolizing of sugars in these drinks by plaque organisms generates organic acids which also leads to demineralization of the teeth and decay (Tahmassebi et al., 2006). Several recent systematic reviews of SSB consumption and oral health (Merugu et al., 2020; Valenzuela et al., 2021) have found robust and positive associations between SSB consumption and tooth decay, as well as a dose–response gradient between these variables (Valenzuela et al., 2021), with a greater frequency of consumption associated with a greater prevalence of oral diseases and higher levels of decay (Merugu et al., 2020). Spatial microsimulation affords the opportunity to assess the spatial patterning of key related variables.

3 | MATERIALS AND METHODS—SIMSHEFFIELD

Data were taken from two sources: the 2011 UK Census of Population (Office for National Statistics, 2011b), and the 2009 Adult Dental Health Survey (ADHS, Office for National Statistics, Social Survey Division, Information Centre for Health and Social Care, 2012). It should be noted that these were the most recently available suitable datasets at the time of building and applying our model and writing this paper. The ADHS is a representative cross-sectional national survey conducted decennially in England, Wales, and Northern Ireland (Scotland conduct their own survey) across 12 strategic health authorities and published in the form of anonymized individual microdata. The ADHS is the most complete source of oral health-related data in the UK, and includes a number of demographic, socio-economic and behavioural variables, allowing it to be used in microsimulation in conjunction with small area statistics from the census. In the 2009 survey, 6,469 adults completed the clinical examination, out of a total sample of 11,380. Nonresponse was accounted for through survey weights to reduce the risk of bias (NHS Digital, 2012a). In one case the 'city dwellers' Output Area Classification group was under-represented in Wales for decay, however, upon further investigation, it was deemed highly likely that this had no impact on the estimate (NHS Digital, 2012b).

SimSheffield is underpinned by iterative proportional fitting (IPF), described as 'a weighting system whereby the original table values are gradually adjusted through repeated calculations to fit the row and column constraints' (Norman, 1999). Constraints are variables that are common to both datasets (usually sociodemographic data). The method was first adopted in a spatial microsimulation framework for synthetic reconstruction of small area microdata using existing small area cross-tabulations (Birkin & Clarke, 1988), and further adopted for combining suitable social survey microdata with small area data (Ballas, 2004; Ballas et al., 2005; Ballas et al., 2007). SimSheffield builds on this work by adopting an IPF-based method known as deterministic reweighting (Ballas et al., 2005), which uses constraint variables as a guide when reweighting microdata in a process in which survey individuals and their associated characteristics are 'weighted up', or replicated, depending on how representative they are of the characteristics of a given area (which, in this case, reassigns respondents from the survey to all Lower Super Output Areas in Sheffield). Once constraint variables are in place, deterministic reweighting is conducted using Formula 1:

Formula 1—Iterative proportional fitting formula

$$n_i = w_i \, \mathrm{x} \, s_{ij} / m_{ij}$$

where n_i is the new weight created for an individual, w_i is the initial weight for an individual, s_{ij} is element $_{ij}$ of table s (small area census data), while m_{ij} is element $_{ij}$ of table m (survey data). A worked example of the IPF procedure is provided in Table 1.

Looking at the population without degrees and with two cars (or vans), there are two such individuals in the survey data (row one, column five), while there are four individuals with these characteristics in the census data (row one, column six). By applying the IPF formula, the original (initial) weight (1) is multiplied by the total from the census (4) over the total from the survey (2). This can be seen in column seven of Table 1, and leaves those without degrees and with two cars (or vans) with a new weighting of 2. Other combinations of education and car ownership have also been calculated.

This indicates that those without degrees and with two cars or vans are more representative than their initial weighting of ‘1’, while also being less representative of this area's population characteristics than individuals with degrees who own two cars or vans (new weight of 6). This process would then loop through the rest of the constraints in order, continuing the process and multiplying the new weight by the one produced in the previous stage. The process then loops back to the first constraint and begins the IPF again (depending on the number of assigned iterations). This adjusts weights of the ADHS records to match small area census population totals (as was also demonstrated in a previous article published in this journal; Campbell & Ballas, 2013), which in this study were Lower Super Output Areas (LSOAs, Office for National Statistics, 2011c). On average these have populations of around 1,500 people. As of the 2011 Census, there were 345 LSOAs in Sheffield. This scale was chosen as it represents small geographical areas but which are large enough to potentially include multiple resources that may be influential in determining health (Broomhead, 2017).

Demographic and socio-economic variables were selected as constraints on the basis of two criteria: having a theoretical link with oral health outcomes and having a statistically significant association with the dependent variable (tooth decay). Six constraint variables were selected and applied in the model in reverse statistical order so that the most influential variable was applied last. This is generally accepted as the best approach (Anderson, 2007). The constraint variables (Table 2), in order of application, were age, gender, education status, National Statistics Socio-Economic Classification (NS-SEC) categories, general health rating, and car ownership. SSB consumption is known to be associated with deprivation (Burt et al., 2006; Warren et al., 2009), and the variable choice for the constraints reflects this, for example, the use of the NS-SEC data, as socio-economic position has been linked to levels of decay (Hobdell et al., 2003; Schwendicke et al., 2015), as has education level (Brennan et al., 2007; Mamai-Homata et al., 2012) and general health data (Bailey et al., 2004; Chroinin et al., 2016). Material circumstances have also been linked to oral health outcomes through use of the Townsend Index (O'Hanlon et al., 1997), where car ownership forms part of this index.

SimSheffield could simulate a large number of target variables (variables of interest to the study) for analysing oral-health-related outcomes (Broomhead, 2017), however, for this research the main target variables were sugary drink consumption and tooth decay scores. Sugary drink consumption was measured using the ‘SofDrnk’ variable,

TABLE 1 Microsimulation reweighting process.

Person	Education	Car ownership	Initial weight	No. in survey	No. in census	New weight
1	Other qualification	2 cars or vans	1	2	4	$1 \times 4/2 = 2$
2	Degree or higher	2 cars or vans	1	1	6	$1 \times 6/1 = 6$
3	Degree or higher	1 car or van	1	1	5	$1 \times 5/1 = 5$
4	Other qualification	2 cars or vans	1	2	4	$1 \times 4/2 = 2$
5	Other qualification	1 car or van	1	1	1	$1 \times 1/1 = 1$

TABLE 2 Constraint data and categorization of variables.

Variable	Groupings
Age	16–24; 25–34; 35–44; 45–54; 55–64; 65–74; 75–84; 85+
Gender	Male; female
Educational attainment	Degree level or above; below degree level
NS-SEC	1.1; 1.2; 2; 3; 4; 5; 6; 7; 8
General health	Very good; good; fair; bad; very bad
Car ownership	Yes; no

which contains details on how often (on average) an individual had 'fizzy drinks, fruit juice, or soft drinks like squash, excluding diet or sugar-free drinks', with the following response options: six or more times a week; three to five times a week; one to two times a week; less than once a week; and rarely or never. The 'Numdu98' variable was chosen to operationalize tooth decay. This continuous variable represents the number of decayed or unsound teeth per person.

The deterministic reweighting (IPF) was conducted using R (Lovelace & Dumont, 2016; R Core Team, 2016) with subsequent analysis conducted in QGIS.org (QGIS, 2020). The model was run for 15 iterations. This resulted in a synthetic small area dataset containing the geographical detail from the census and individual-level details of the ADHS, allowing for analysis of policy scenarios related to socio-economic and health-based outcomes. The model was internally validated using conventional approaches (Lovelace & Dumont, 2016), including calculating a Pearson's r coefficient, which, with a score of 1, indicated excellent convergence between Census and ADHS data (Figure 1).

The total absolute error (TAE) and standardized absolute error (SAE) were also calculated. The TAE is a measure of the absolute difference between the census and simulated data for each LSOA, while the SAE divides the TAE by the population of a given LSOA. The TAE and SAE scores were 0.2985 and 0.0000001101, respectively, indicating very low levels of error. Additionally, two-tailed equal variance t-tests were conducted to indicate any statistically significant differences between the census and simulated data (Edwards & Clarke, 2007). No significant differences were found for the overall model or individual constraints (Table 3).

The data were also externally validated against variables not used as constraints, but still common to both the census and ADHS (ethnicity and marital status). This approach has been used previously to validate spatial microsimulation models (Campbell, 2011) by taking aggregated estimates from the spatial microsimulation model at LSOA level (and the associated target variables such as ethnicity and marital status) and comparing these with corresponding census estimates. Two statistical measures were used (Table 4): the R^2 value, which measures the fit of the data, but not necessarily around a given point, and the standard error around the identity (SEI), which measures how well data fits the 45-degree line (Tanton et al., 2011).

While results of the external validation were mixed, most variables achieved an R^2 value above 0.5, with SEI scores near to this figure. Some of the lower R^2 and SEI values may be partly explained by the lower counts of some variables (e.g., civil partnership). In these cases, any variance between simulated and observed data will have larger proportional impacts than in cases of variables with larger counts. Previous research has commented on similar issues regarding validation and small numbers (Burden & Steel, 2016).

Consideration was given to validating the model against other sugar-based variables within the ADHS, however, these were not directly comparable to the sugary drink consumption variable, as they represent different types of sugar consumption and intake. These included questions on how often participants ate cakes or sweets and whether they had sugar in hot drinks. A fourth question on whether participants had a high sugar intake had a binary response format ('high sugar intake' versus 'not high'), and therefore lacked the granularity of the sugary drink consumption variable, making it unsuitable for comparison. In addition, these questions were not included in the census, which is required for validation if the aggregated results of the spatial microsimulation (and the associated target variables of interest) are to be compared with the census estimates for that variable. Data on SSB consumption from other sources were presented at the national level without appropriate disaggregation (geographically or consumption frequency), and no other national-level surveys contained information on SSB consumption that was comparable to the ADHS.

4 | USING SIMSHEFFIELD TO ASSESS POTENTIAL IMPACTS OF THE SOFT DRINK INDUSTRY LEVY

This section focuses on the spatial patterning of individuals in the microsimulation dataset and the key outcome variables: sugary drink consumption and tooth decay. Tooth decay scores for each LSOA will be presented first to

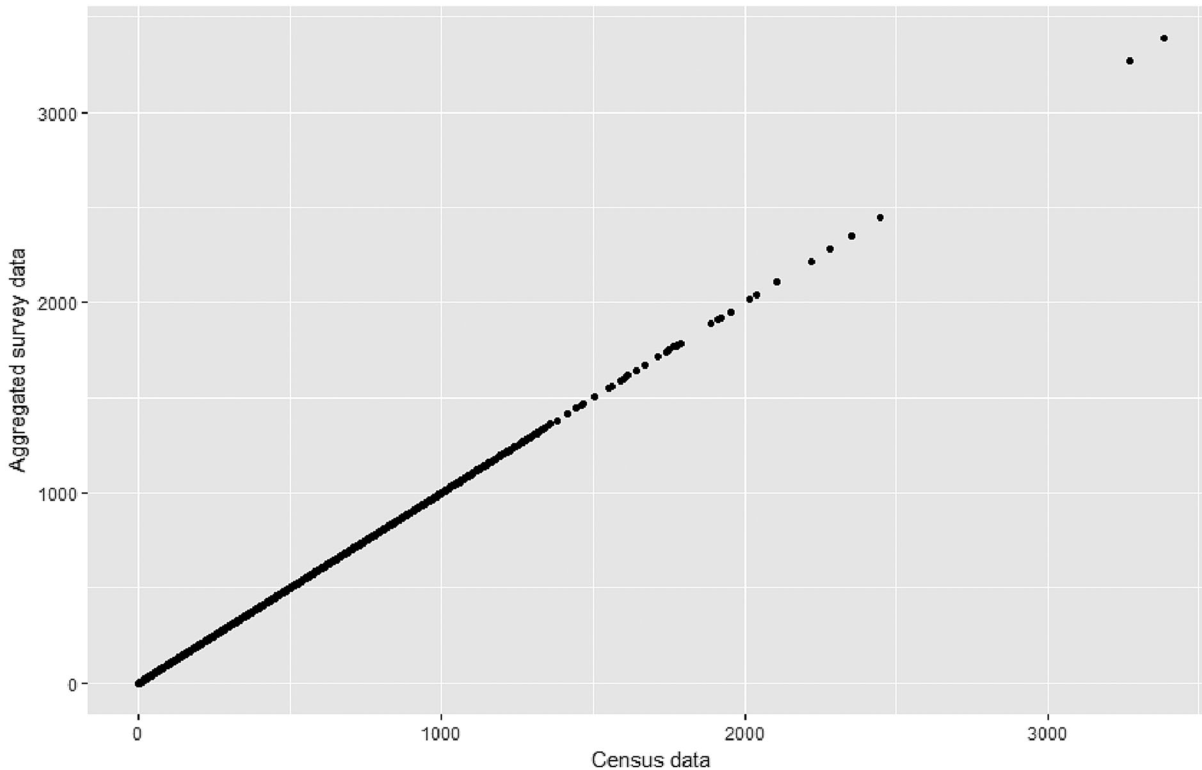

FIGURE 1 Convergence between the census data and the adult dental health survey.

TABLE 3 Results of two-tailed equal variance *t*-tests.

Constraint	*p*-Value
Overall model	0.9950
Age	0.9996
Gender	0.9993
Educational attainment	0.9998
NS-SEC	0.9995
General health rating	0.9998
Car ownership	1

TABLE 4 Results from the external validation of SimSheffield.

Validation variable	R^2 value	SEI value
Marital status, single	0.97	0.95
Marital status, married	0.82	0.73
Marital status, civil partnership	−0.006	−0.28
Marital status, separated	0.32	−0.13
Marital status, divorced	0.63	0.6
Marital status, widowed	0.88	0.7
Ethnicity, white	0.53	0.44
Ethnicity, mixed ethnic group	0.36	−0.44
Ethnicity, other ethnic group	0.6	0.27

provide the spatial context for this disease within Sheffield. Subsequent analysis will visually depict levels of sugary drink consumption in the city, before presenting an analysis of areas most likely to be impacted by the SDIL.

4.1 | Tooth decay in Sheffield

Figure 2 shows the SimSheffield output for tooth decay at the LSOA level. The total number of decayed teeth in each LSOA was divided by the population of each area to give a mean number of decayed teeth, in line with the way decay is commonly measured in dentistry and dental public health. The average number of decayed teeth ranged from 0.71 to 1.63, with an average of 1.04 for the city, with 40.9% of adults experiencing decay of some kind. Within Sheffield, LSOAs with the highest average levels of decay were situated to the east of the city, while levels of decay were, on average, much lower in the west. This is not surprising given the spatial patterning of Sheffield's industrial history, with areas of heavy industry located in the east along the Don Valley, with workers often situated nearby, and more affluent residents living in the west nearer the Peak District. This pattern still manifests itself in sociodemographic, economic and health-related outcomes (Thomas et al., 2009). It is worth remembering that large areas to the west of the city, and some of the larger LSOAs in size, are rural areas in the Peak District, and will therefore have much smaller populations compared with more built-up areas within the city. Previously data on tooth decay in adults with this level of geographically disaggregated detail would not have been available, and demonstrate the benefits of the spatial microsimulation approach for assessing geographical differences in disease outcomes for small area geographies.

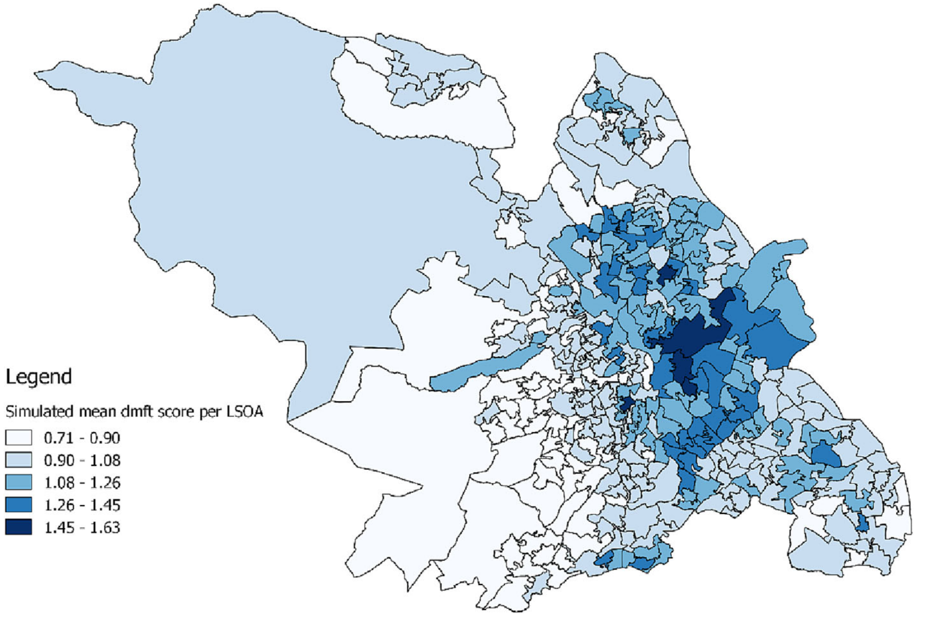

FIGURE 2 Simulated mean number of decayed teeth per LSOA in Sheffield.

4.2 | Sugary drink consumption in Sheffield

Figure 3 shows simulated proportions of residents in each LSOA that consumed sugary drinks six or more times per week. The highest consumption quintiles are located near the city centre, as well as some of the western suburbs. Across the rest of Sheffield there is a relatively low proportion of individuals consuming sugary drink six times or more a week. While it might be expected that areas of higher deprivation would have a higher consumption of sugary drinks (Burt et al., 2006; Warren et al., 2009), the areas with highest consumption coincide with sites associated with the city's two universities and areas where student residences are more prevalent. There are also a number of more deprived inner-city areas that have higher SSB consumption, which may add to this pattern. Despite lower proportions of residents consuming sugary drinks six or more times a week outside of the city centre and western suburbs, some LSOAs to the east and north of the city centre showed an increased level of consumption compared with other parts of the city. These LSOAs are located in some of the less affluent areas of the city such as Manor, Firth Park, Parsons Cross and Southey Green. From this simple map it is possible to see where those who may be most affected by a levy on SSBs are located.

Figure 4 shows a similar pattern, with more central areas of the city and those near to universities and university accommodation having a higher proportion of residents consuming three to five sugary drinks per week. However, there appears to be a more widespread pattern of consumption of sugary drinks across the city for this response option than in Figure 3. While many of these areas are in the east of Sheffield, there is also a large number located in the more affluent suburbs to the west of the city centre.

The findings from Figures 3 and 4 contrast with those of Figure 5, which show the patterning of those answering 'rarely or never' to weekly sugary drink consumption. This shows that other than in central and eastern areas of the city, most of the LSOAs contained a high proportion of residents who rarely or never consumed sugary drinks. Again, areas with a lower proportion of residents rarely or never consuming sugary drinks were situated in the city centre, and surrounding areas often associated with the city's universities. There was also a notable cluster of LSOAs in the east of the city, particularly running along the old industrial heartland of the Don Valley, which exhibited very different patterns to most of Sheffield and contained LSOAs where a lower proportion of residents would rarely or never

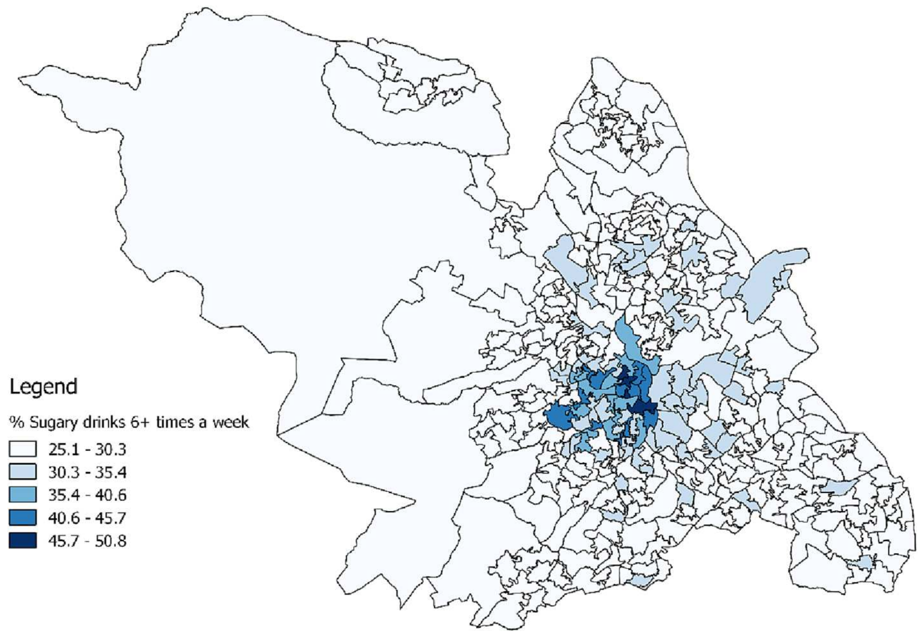

FIGURE 3 Simulated consumption of six or more sugary drinks per week.

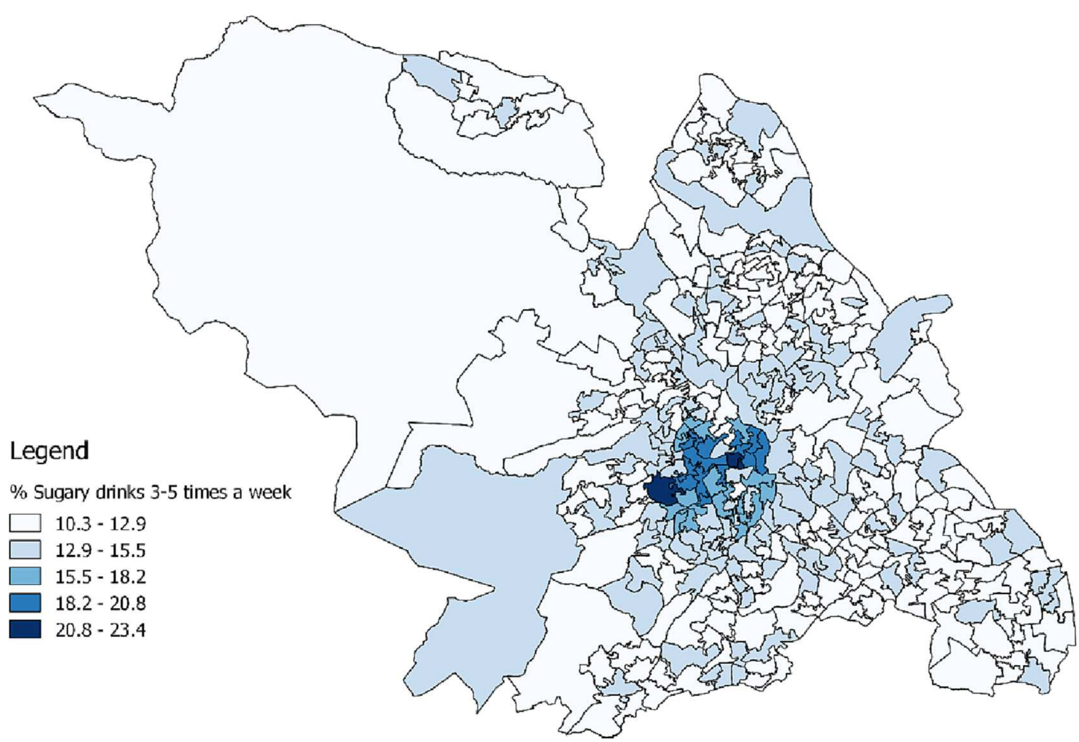

FIGURE 4 Simulated consumption of three to five sugary drinks per week.

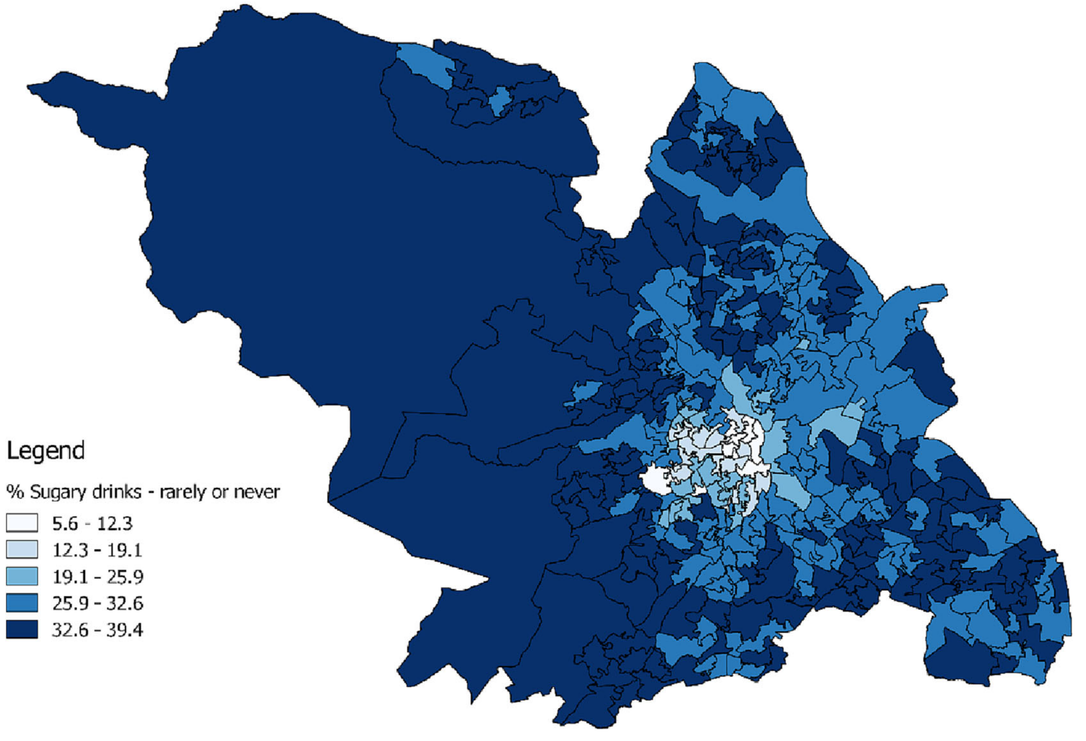

FIGURE 5 Simulated data for those consuming sugary drinks 'rarely or never'.

consume sugary drinks. Comparatively, many LSOAs in the western suburbs of Sheffield have, on average, a higher proportion of residents who rarely or never consume sugary drinks each week.

The data show a pattern of LSOAs in the city centre, and some nearby areas, exhibiting higher levels of sugary drink consumption per week compared with the rest of the city. This information could help to further understand where, as well as which types of people, may be affected most by policies such as the SDIL.

4.3 | Modelling the spatial effects of the soft drink industry levy

It is worth noting that the following is not designed to be an in-depth analysis of every aspect of the SDIL, but rather an example of how spatial microsimulation can aid in understanding potential spatial patterning of the effects of such policies. Given the categorical nature of the responses to sugary drink consumption in the ADHS, several assumptions were made. Individuals responding 'rarely or never' were given a score of zero, 'less than once a week' a score of 0.5, 'one to two times a week' a score of 1.5, 'three to five times a week' a score of four, and 'six or more times a week' a score of six. While it is likely individuals in the last category may consume more than six sugary drinks a week, there is no way to tell what this figure is, so the more conservative estimate of six was used.

Given the tax rates described in Section 2, the price of a 330-mL can containing more than 8 g of sugar would increase by eight pence (rounded up from 7.92 pence), while a 500-mL bottle containing more than 8 g of sugar would increase by another 12 pence. Figure 6 demonstrates the average amount of extra tax that would be paid per week, on the basis of consuming 330-mL cans of sugary drinks. The analysis focuses only on additional tax, as base prices for soft drinks may vary geographically and taking average prices could obscure local variations. As seen in Figure 6, LSOAs in the centre of Sheffield and to the west of the centre, and to a lesser extent LSOAs in the east of

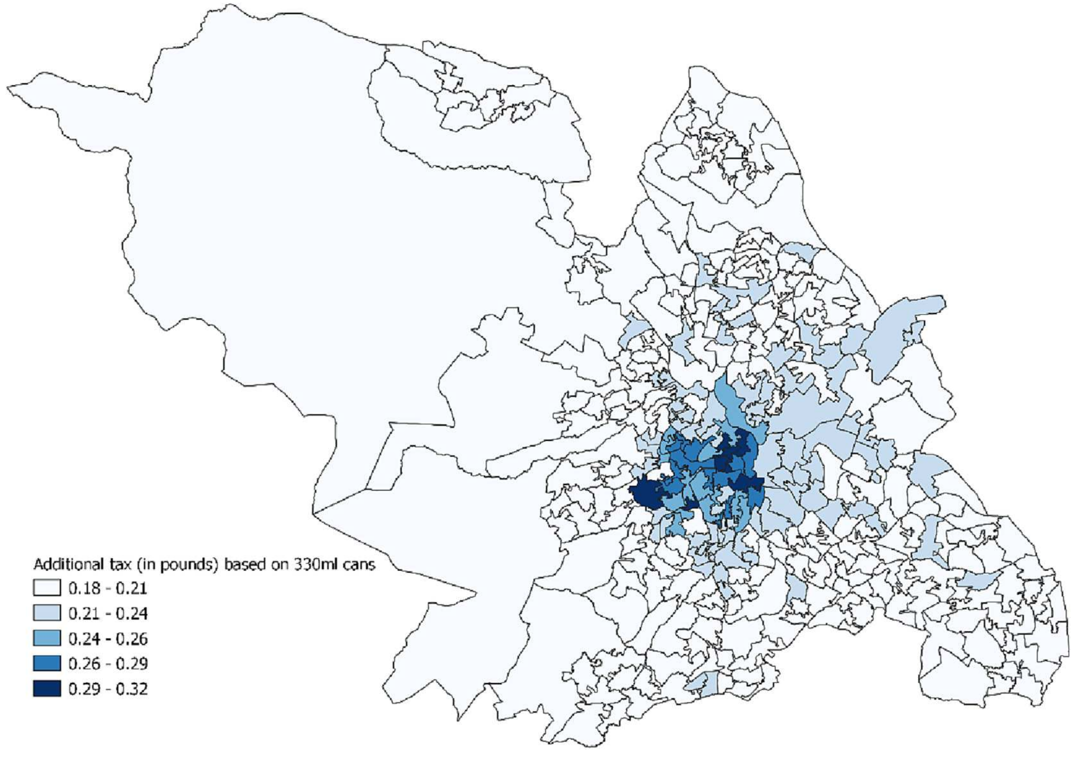

FIGURE 6 Estimated average additional tax per LSOA in Sheffield.

the city, would on average see the greatest impact of the SDIL. This is not surprising given the patterns seen for sugary drink consumption in Figures 3 and 4. This demonstrates differences of between 8 pence and 14 pence per week between the most and least affected areas, leading to potential differences in tax, ranging from £9.36 to £16.64 (on average) per year between these areas. This pattern is repeated for consumption of 500-mL bottles of sugary drinks, as simulated individuals have the same consumption rate of sugary drinks per week, with tax being the variable changing depending on the size of sugary drinks consumed. In this case, the tax bands (lowest to highest) were: 0.27–0.31; 0.32–0.35; 0.36–0.39; 0.40–0.44; and 0.45–0.48. This represents potential differences of 13–21 pence per week between the least and most affected areas, and potential differences in tax ranging between £14.04 and £24.96 (on average) per year.

These numbers are based on individual cans or bottles, and it may be that individuals would buy larger volume drinks, such as 1.5-L or 2-L bottles. In the case of a 2-L bottle, this would lead to increases in price of 48 pence per bottle (on the basis of the 24 pence per litre taxation rate of the SDIL). If we assume individuals with a score of zero drinks per week will not buy any, and that individuals with scores of 0.5 and 1.5 are more likely to buy cans (due to lower overall consumption), while those consuming sugary drinks four or six times a week may opt to buy larger bottles, we can look at the differences between these groups in terms of SDIL impact. Figure 7 demonstrates a pattern that is almost identical to Figure 6, except for slight increases in tax for each category (3–4 pence). This demonstrates that even when paying for the highest taxable products under the SDIL, and for those who consume sugary drinks the most, the pattern does not change. Again, this is perhaps not surprising, given that consumption rates remained the same across individuals/areas, and only tax levels varied. This scenario represents a potential tax range of £10.92–18.72 (on average) between the least and most affected areas. It is worth remembering with all these scenarios that use of average sugar consumption and tax data may be obscuring more extreme values, and that some individuals may be paying far more/less than average values.

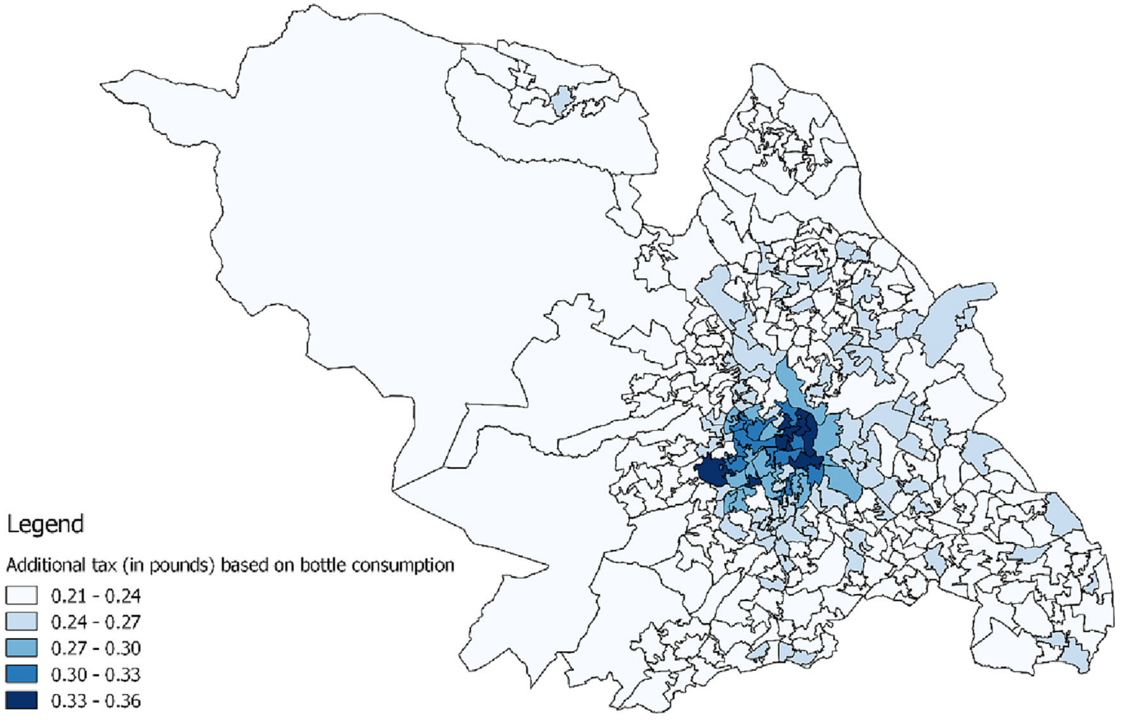

FIGURE 7 Estimated average additional tax per LSOA in Sheffield, including 2-L bottles for those drinking sugary drinks four or six times a week.

Figures 6 and 7 demonstrate that areas in the city centre and to the west of this, as well as areas to the east of the city (which are on average more deprived) would be impacted to a greater extent by the tax. However, a closer inspection of the data reveals some interesting patterns. The LSOAs with the highest tooth decay and deprivation scores are not always the most impacted by the SDIL. As can be seen in Figures 8 and 9, LSOAs most affected by the SDIL are in the city centre, as well as areas to the west of the centre. Conversely, LSOAs with higher deprivation levels (Figure 8) and tooth decay (Figure 9) are located to the east of the city. This suggests that deprivation and tooth decay may not always be associated with the impact of the SDIL. There are several LSOAs in central Sheffield that are among the more deprived in the city, however, the majority of LSOAs that are impacted to a greater extent by the SDIL are among the least deprived. It is notable that a number of these LSOAs are in areas near the city's universities and associated student residences. Demographic profiles of these areas (students or age profile) may be influencing these patterns. It is also possible that individuals living in more central areas have greater access to sugary drinks through the number of shops and supermarkets that are present. Overall, this highlights the complexity of these relationships, which warrant further investigation to understand mechanisms occurring at small area levels.

5 | DISCUSSION

This analysis demonstrates the benefit of spatial microsimulation for investigating small area differences in oral health and the potential impact of national policies. To the best of our knowledge, this is the first study to use this approach to analyse oral health inequalities in this way. SimSheffield produced individual data for tooth decay scores and sugary drink consumption, which previously would not have been available in this detail by LSOA or other small area census geographies.

FIGURE 8 Comparison of city centre maps for SDIL (left) and deprivation (right). *Source*: *OpenLayers plugin—Sourcepole.

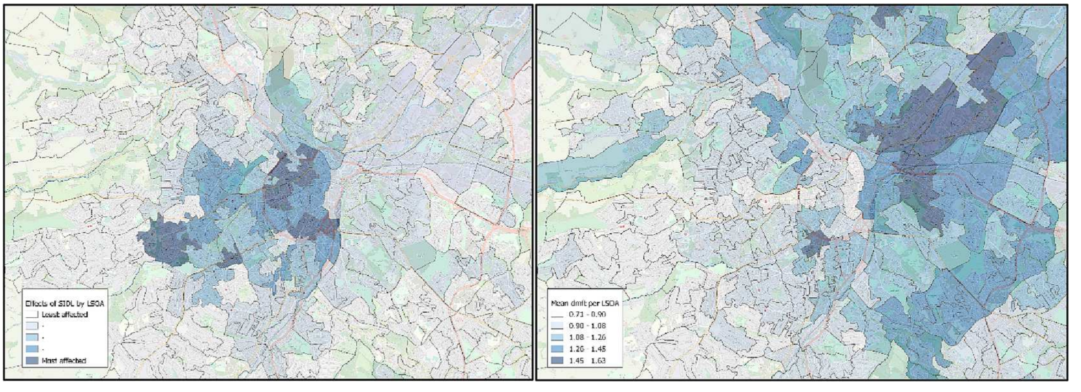

FIGURE 9 Comparison of city centre maps for SDIL (left) and tooth decay (right). *Source*: *OpenLayers plugin—Sourcepole.

The analysis produced some interesting results, particularly that higher levels of soft and sugary drink consumption occurred in areas of the city with lower mean tooth decay scores. This may be due to the profile of these areas, and highlights the complex nature of the determinants of tooth decay. While soft and sugary drinks are known to be important for this (Burt et al., 2006; Sheiham, 2001; Warren et al., 2009), there are likely other determinants playing equal or more important roles. These determinants may be related to food and drink consumption, individual behaviours and habits, dental service locations, or other features of neighbourhood environments. They may also be related to the demographic profile of the residents. For example, some of the areas of the city where there are lower tooth decay scores and high levels of soft and sugary drink consumption have large university student populations who come from a variety of differing geographical locations and may have socio-economic and demographic profiles different from permanent populations in the city. Frameworks such as those proposed by Macintyre et al. (2002) suggest it is likely a combination, as these situations are often complex in nature (Broomhead & Baker, 2019).

From a socio-spatial justice and policy perspective, it is interesting to note that areas with higher deprivation scores were not associated with the largest SDIL impacts (in the raw amount of extra tax paid), as might have been hypothesized on the basis of existing literature. This is not to say that these areas are not significantly affected in terms of the income impact, as individual and household income (among other potentially important determinants) and the proportional effect of this tax were not included in the model due to the high number of missing values for income data in the ADHS. As referenced earlier, if SSB consumption is higher in more affluent LSOAs, residents of these areas may be able to afford this increase compared with lower income areas (Riediger & Bombak, 2018), leading to potentially unequal impacts. There were also a number of less affluent LSOAs near the city centre with higher SSB consumption which may be hit harder by the levy. Again, this highlights the complexity of these situations and the need for further investigation of relevant patterns and mechanisms. Use of dynamic simulation modelling in particular may give better insights into future trends associated with these variables.

6 | CONCLUDING COMMENTS

The study presented in this article aimed to demonstrate how the SimSheffield data provide a powerful resource for investigating policy-related patterns in relation to socio-economic and health-based outcomes and could be beneficial to the field of dental public health. Spatial microsimulation can aid in other ways, as its base data can be used in other quantitative and statistical analyses, as well as in forming the base of agent-based models (Ballas et al., 2019). Additionally, spatial microsimulation can contribute to theoretical work by producing rich-in-detail datasets of representative individuals with behaviours, attitudes, socio-economic backgrounds and oral health outcomes to aid in operationalizing and testing theoretical frameworks (Broomhead, 2017). Extra target variables added to the analysis can be matched against theoretical concepts in a given framework for which there is a lack of real-world data. Investigating the social determinants of health, for example, would require a mix of sociodemographic, economic and health-based variables, while other complex issues would similarly require a mix of variable types (Broomhead et al., 2019). Spatial microsimulation is therefore useful for investigating areas where limited or no data are currently available.

Strengths of the analysis include the use of an established and reliable population synthesis method with the flexibility to combine population counts from census data with behavioural and clinical survey data. While this method cannot account for interactivity, it includes 'important statistical mechanisms … [which] ensure the similarity of what it predicts and what is actually observed in the data' (Wu et al., 2008).

This study has several limitations which should be considered in the context of the results. While external validation of SimSheffield generally performed well, the relatively low sample size of the AHDS survey means the data produced by the spatial microsimulation modelling should be treated with a degree of caution. In particular, it should be noted that the lower sample size from the ADHS is especially relevant to key variables used in this study. Due to only 6,469 individuals (out of 11,380) undergoing a clinical examination, and after having to remove missing data, only 4,414 records were included in the data synthesis. Previous research has noted that 'as sample size increases, resulting population experience gains in accuracy' (Ryan et al., 2009). Larger sample sizes may therefore have benefited model accuracy. Additionally, several assumptions were made when assessing potential effects of the SDIL, including assigning numeric values to categorical answers, which may deviate from real-world patterns. Additionally, base prices for soft drinks, and geographical variation in these, were not included in the analysis.

In addition, there is considerable room for improvement regarding the validation approach that we adopted to have a better measure of uncertainty. To that end, there is great potential to utilize and build on the innovative work of Whitworth et al. (2017), who presented a method that can be used to build credible confidence intervals around spatial microsimulation estimated values. Finally, the age of the datasets used in the analysis must be acknowledged. More recent national oral health surveys or census data are not yet available in the UK, and due to the need to match the two datasets (needing to be similar to each other in the year they were collected) the 2009 ADHS and 2011 Census were used. It is likely that patterns of oral health and sociodemographic data have changed since these data were collected, and this should be borne in mind when considering the analysis.

Nevertheless, despite the limitations, the study presented in this article clearly demonstrates the strong potential of spatial microsimulation for oral health socio-spatial policy analysis (building on the already established literature and applications of spatial microsimulation in regional science and policy). In particular, this paper demonstrates the benefits of spatial microsimulation in producing previously unavailable data (which can be generated at differing geographical scales depending on the type of spatial data entered by the user), and in assessing potential spatial and socio-economic impacts of policies. Analysis of sugary drink consumption and taxes associated with the SDIL revealed that areas in the city centre and western suburbs were most affected. This did not match the patterning of tooth decay and deprivation, suggesting the need to consider and include other mechanisms and variables which may be important in determining sugary drink consumption.

Despite the results of this analysis, and calls from within oral health research for the control, limitation and management of SSB intake (Merugu et al., 2020; Valenzuela et al., 2021), the question of whether the tax is fit for purpose is one that can only be answered through longer-term data collection and analysis. As has been highlighted, the timescale involved in the development of tooth decay, and the nature of structural projects such as SSB taxes, means it will take time before we can be certain what the impact of these interventions are (Broomhead & Baker, 2023). In the meantime, spatial microsimulation offers an opportunity to assess the potential effects of such interventions on relevant populations.

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