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OBESITY AND URBAN FORM: EVIDENCE FROM LONDON

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OBESITY AND URBAN FORM: EVIDENCE FROM LONDON

Abstract:. *This paper examines the association between urban form and obesity rates at the neighbourhood level. Using data from London, UK in a regression and mediation analysis framework, we find that high population density, more diverse land use, better public transport access and higher street connectivity are all associated with lower obesity rates after controlling for a range of possible confounders such as income, unemployment, education and age. These findings corroborate and extend the existing empirical evidence on the crucial role of neighbourhood factors, in particular built environment factors, in counteracting rising obesity levels in large cities and metropolitan areas.*

Keywords: *Obesity, urban form, land use mix, street connectivity, mediation analysis*

INTRODUCTION

Obesity has been identified as a key public health concern in virtually all affluent contemporary societies. The United Kingdom is a prime example of this trend. In 2014, 58% of women and 65% of men were overweight or obese. Prevalence of the condition has nearly doubled in the last two decades and morbid obesity rates, the most severe form, has tripled (Health and Social Care Information Centre 2015). The United Kingdom now has the highest obesity levels in Western Europe. These figures paint a bleak picture with multiple ramifications for public health and future healthcare spending. The health implications of obesity have been widely researched, highlighting direct links to a host of illnesses such as cardiovascular disease, diabetes, hypertension, osteoarthritis and several forms of cancer (Must et al. 1999). Furthermore, Mckinsey (2014) predict that the economic cost of obesity borne by the UK National Health Service (NHS) could rise to £12 billion per annum by 2030. The literature on the physiological pathways leading to obesity and the connection between diet and obesity are well established. What is only vaguely understood and therefore contested among researchers is the contribution of an individual's environment, notably urban form, to excessive weight gain. The present paper seeks to shed light on this question by examining a comprehensive dataset from London, UK which includes a range of urban form features such as population density, land use mix, street connectivity and public transport accessibility as well as socio-economic variables such as income, unemployment, education and age. The contribution of each of these factors is then estimated with a linear regression model and a mediation model. The findings show clear associations between urban form characteristics and obesity prevalence, adding further empirical evidence to this growing strand of literature.

LITERATURE REVIEW

The effect of urban form on public health has been a concern of planners and policymakers at least since the Industrial Revolution and its concomitant rapid urbanisation. Lopez (2007) notes that much of urban policy in the late 19^{th} and early 20^{th} centuries focussed on reducing population density to alleviate overcrowding, tuberculosis and other detrimental effects to the health of city dwellers. More recently, the argument appears to have reversed as the effects of low-density suburban living and its potential effects on obesity rates have come under close scrutiny. The London agglomeration provides a vivid example of this trend. Historical census data from 1931 to 2001 document a pronounced long-term decline in density from 5160 persons/km^2 to 4562 persons/km^2 in the 70-year time span. Its inner city population fell by 26% while suburban areas grew by 42% (Census Information Scheme 2015).

The existing literature on the built environment and obesity is extensive, with the majority of research focussing on the USA. The rise of the New Urbanism movement has ushered in a wave of criticism against Western planning regimes dating back to the 1950s, particularly due to their support of low-density expansion at the urban fringe. Cervero & Gorham (1995) indicate how sprawled environments frequently suffer from a lack of cycle paths and pavements, as these neighbourhoods are primarily designed to accommodate for vehicular transportation. Indeed, a collection of further research supports this idea, arguing that the very layout of sprawled suburban settlements is conducive to the promotion of sedentary lifestyles by means of discouraging physical activity (Boarnet et al. 2000, Hess et al. 1999, Handy 1996). When focussing the discussion back to London in particular, Cozens & Hillier (2008) raise the issue of The Garden City movement conceived in the late 19th century, arguing that it contributed to the multitude of noxious effects produced by urban sprawl. They cite the example of Hampstead Garden Suburb, located on the periphery of North-West London, whose formation of cul-de-sac streets serves to elevate both travel times and distances, in turn lowering walkability within the area.

There has been considerable public health research into the ways in which the amenities of a built environment can influence obesity outcomes within a population. In an Australian cross-sectional study, Giles-Corti et al. (2003) disclose a positive correlation between the distance from one's home to the nearest recreational/sports facility and the risk of being obese. Moreover, the aesthetic and social aspects of built environments have been shown to alter levels of neighbourhood physical activity and obesity. In a similar vein to Jane Jacobs' 'Eyes on the street' theory, Weir et al. (2006) use a questionnaire based survey to illustrate how individuals from neighbourhoods with high crime rates tend to engage in less physical activity than their counterparts in safer neighbourhoods. This has been attributed to the perceived fear of violence and gang aggression which discourages people from spending time outdoors.

When considering the consumption of food in the home, it becomes clear that dietary patterns are found to be closely associated with the geographical location of food retailers (Glanz & Yaroch 2004). This idea is confirmed by Morland et al. (2002), who show that daily fruit and vegetable intake rises correspondingly as the density of supermarket outlets within a census tract increases. It is also interesting to note how socioeconomic factors can play a role in influencing food environments. Morton &

Blanchard (2007) elucidate the concept of 'food deserts', in which low income neighbourhoods are often chronically lacking in fresh food grocers. This factor has been hypothesized, in part, to mediate the relationship between poverty and obesity prevalence. Following on from this, Zenk et al. (2005) depict the ethno-geographic inequalities rife in Detroit, in which white neighbourhoods are, on average, 1.1 miles closer to the nearest supermarket than African-American neighbourhoods. Freudenberg et al. (2010) report that low-income neighboorhoods have a variety of characteristics which encourage low activity and higher obesity rates such as fewer parks and recreation facilities, higher levels of street crime and heavy traffic.

Perhaps the most prominent large-scale study was conducted by Ewing et al. (2003), who use cross-sectional ecological modelling to assess the link between urban sprawl and obesity related outcomes, based on BMI. Their findings indicate a positive relationship between sprawl and BMI, whereby after controlling for individual factors, residents living in a county one standard deviation below the mean county sprawl index were only 0.9 times as likely to be obese than those living in a more sprawled county one standard deviation above the mean.

Whilst there is a large body of literature supporting an association between urban sprawl and obesity, there has been significantly less work focussing on the causal links of this relationship. Indeed, several prominent papers within this field allude to the idea of physical activity as a factor which controls the relationship between the two variables, yet they fail to actually examine this notion empirically (Bodea et al. 2009, Gregson 2011, Brown et al. 2009). It is therefore challenging for previous research to contribute to policy decisions, as researchers haven't fully highlighted the pathways which link the built environment to obesity outcomes.

RESEARCH DESIGN

The empirical analysis presented in this paper consists of two steps: (i) assessing the direct links between London's built environment and rates of obesity and (ii) identifying the possible mediators of this relationship. The following sections describe for each of these two analytical steps separately the datasets, sampling methodology as well as the variable definitions and justification for inclusion in the analysis.

I) ASSESSING THE DIRECT LINKS BETWEEN LONDON'S BUILT ENVIRONMENT AND RATES OF OBESITY

The analysis conducted in this study comprises a cross-sectional multi-linear regression analysis. This method facilitates investigation into to which built environment factors are significantly associated with obesity in the capital city, as well as enabling the model to control for socioeconomic variables. The four built environment factors that have been investigated are population density, land use mix, street connectivity and public transport accessibility. The four control variables are income, unemployment, education and age.

DATA & SAMPLING

The type of geographical unit that should be employed for data analysis is an important consideration for any spatial study, particularly if it involves individual level data such as obesity. This study analyses data at the smallest geographical unit available - Middle Layer Super Output Areas (MSOAs), in order to improve accuracy compared to more aggregate datasets. London contains 983 MSOAs which each have a population ranging from 5,000 to 15,000 people. Table 1 contains a full list of sources and descriptive statistics.

TABLE 1: DESCRIPTIVE STATISTICS

Variable	Measurement	Data Source	Range	Min.	Max.	Mean	Std. Deviation
Obesity Prevalence	% of MSOA population who are clinically obese (BMI > 30)	ONS Modelled Estimates 2008	24.1%	9.8%	33.9%	21.1%	5.4%
Built Environment Predictor Variables							
Population Density	Persons/Hectare^2 (measured in hundreds) – based on place of residence	ONS Census 2011	2.52	0.03	2.55	0.85	0.49
Public Transport Accessibility	Public Transport Accessibility Levels (PTALs)	Transport for London 2014	6.74	1.26	8.00	3.75	1.42
Street Intersection Density	Number of Street Intersections/Hectare^2	Ordnance Survey Integrated Transport Network Layer 2016	9.53	0.13	9.67	2.07	1.63
Land Use Mix	Land Use Mix Entropy Formula (See Methodology)	DCLG- Generalized Land Use Database 2005	1.00	0.00	1.00	0.54	.18
Socioeconomic Predictor Variables							
Income	Median Household Income (measured in £ thousands)	ONS Census 2011	72.12	17.88	90.00	35.24	10.70
Unemployment	% of MSOA population who are unemployed	ONS Census 2011	14.9%	2.5%	17.4%	7.4%	2.9%
Education	% of MSOA population with Level 3 Qualifications or Higher	ONS Census 2011	55.0%	15.0%	70.0%	38.6%	11.9%
Age	% of MSOA population over the age of 65	ONS Census 2011	24.2%	3.1%	27.2%	11.4%	4.1%
Mediator Variables							
Weekly Physical Activity	% of MSOA population (16+) engaging in (sports/leisure) physical activity for 30 minutes at least three times per week	Sport England - Active People Survey 2012	31.0%	15.5%	46.5%	26.0%	5.6%
Active Commuting Patterns	% of MSOA population who commute by active transport (walking or bicycle)	ONS Census 2011	60.2%	3.3%	63.5%	14.6%	8.4%
Fast Food Outlet Density	Number of Fast Food Outlets/Hectare^2	Ordnance Survey Points of Information Overlay 2011	7.47	0.00	7.47	0.10	0.31

ONS Census 2011

Population Density

The existing body of literature supports findings of an inverse association between population density and obesity prevalence (Feng et al. 2010). Reasons for this relationship emanate from both physical activity and food environment possibilities. High levels of population density have been shown to reduce vehicular transport and raise levels of walkability within neighbourhoods, thus lowering the prevalence of obesity. Lopez & Hynes (2003) endorse this view in a nationwide US study. From the food environment perspective, research also illustrates that densely populated areas are often accompanied by greater accessibility to healthy food outlets which sell fresh fruit and vegetables (Rundle et al. 2009). In this study, population density was denoted as the number of residents per square hectare.

Land Use Mix

It is frequently hypothesized that a blend of different land uses can incentivize physical activity and thus reduce levels of obesity. This is because residents can walk to different functions located in close proximity of one another, such as restaurants, places of work and retail (Owen et al. 2007). Mobley et al. (2006) support this notion empirically in an Australian study, finding that women living in mixed land use environments have an average BMI which is 2.6 kg/m^2 lower than women living in single use residential areas.

Data for the land use mix variable was selected from the Generalised Land Use Database (DCLG 2005). This data set gives an insight into the amount of space (m^2) in each MSOA that is dedicated to a particular land use, and hence it was possible to compute the relative percentages occupied by the three main urban land functions: residential, office and retail. An entropy formula, proposed by Leslie et al. (2007), was then employed to ascertain the level of heterogeneity amongst the different land uses, in which K is the type of land use, N is the number of land uses (in this case 3) and P is the percentage of an area devoted to land use K. A score of 0 indicates total homogeneity of just one land type, whilst a figure of 1 indicates equal distribution amongst all three land uses.

$$-\frac{\Sigma_k (P_k \ln P_k)}{\ln N} \tag{1}$$

Street Intersection Density

From a theoretical viewpoint, environments with high levels of street connectivity ensure that destinations can be reached with shorter, quicker routes, which could incentivise walking. This may in turn lead to residents engaging in more physical activity, thus serving to curb rates of obesity. Following the approach of Burgoine et al. (2011), ArcGIS was employed to create a digital rubric of London's streets, The base map comprised an OS MasterMap together with an OS Integrated Transport Network (ITN) layer, following which it was possible to plot all street intersections onto a base map. The number of intersections in each MSOA was later summed and divided by the geographical size of the area. This produced a street connectivity number for all 983 MSOAs, measured as number of street intersections/hectare^2.

Public Transport Accessibility

Several recent studies have attempted to reconcile the relationship between public transport use and obesity outcomes. In a contemporary Australian study, Bus Association Victoria (2010) propose the notion that commuting by public transport can increase physical activity by up to 33 minutes per day, hence lowering overall levels of BMI. The source of this physical activity stems from the walking required at the beginning and end of the trip, as well as when changing routes, such as walking from a bus stop to a train platform. Consequently, when one considers the built environment, it can be posited that areas with strong accessibility to public transport are associated with reduced rates of obesity.

In order to quantitatively evaluate the connectedness of London's MSOAs to public transport links, this study chose to adopt a proxy of PTALs. Calculated by Transport for London, PTALs (Public Transport Accessibility Levels) calculate average walk times to public transport nodes within an MSOA, encompassing bus stops, train stations, tube stations and Tram links (TFL 2010). The rationale behind this indicator is to proxy the total time involved in taking public transport, whereby a figure of 0 suggests poor accessibility and a score of 8 denotes superlative accessibility, which could in theory promote public transport use and hence physical activity.

Whilst this study aims to explore the relationship between the built environment and obesity outcomes, it is important to recognize and control for the presence of external factors which can also impact upon the dependent variable. In an extensive review of the literature, McLaren (2007) illustrates the network of complex socioeconomic factors which serve to influence patterns of obesity. Suglia et al. (2016) also stress the crucial role of social neighbourhood environments in obesity outcomes.

Income

The negative link between income and obesity has been well established (Stunkard 1996). This trend was recently confirmed in a British study which found that 22% of children in the lowest income quintile were obese, whilst this figure fell to just 7% amongst the highest income quintile (HSCIC 2015). Explanations of this relationship tend to revolve around diet quality, whereby higher income individuals are able to afford fresh fruit and vegetables required for healthy nutrition. Conversely, families in socioeconomic deprivation are often forced out of this market, instead having to resort to cheaper alternatives such as processed foods that are high in saturated fats (Power 2005). In this paper, the income variable will be taken as Median Household Income (£).

Unemployment

Rates of unemployment have been shown to be negatively correlated with obesity levels. In a Canadian study, Janssen et al. (2006) find that the odds of being obese were 74% greater in areas of high unemployment (>9.0%) versus areas of low unemployment (<5.5%). Similar to income levels, the relationship between unemployment and obesity is often attributed to the inability of individuals to afford healthy food required for a balanced diet (Burns 2004). Interestingly though, the causality of this link has also been suggested to function in the other direction. Morris (2007) shows that living with obesity can make it more challenging to find a job given the presence of potential employer discrimination.

Education

Previous research has suggested an inverse relationship between levels of education and obesity outcomes. Devaux et al. (2011) support this notion on the grounds that educated people are more likely to have greater information and knowledge when making decisions related to food choice. This includes being aware of the nutritional content found in different food groups, thus enabling individuals to more easily select balanced diets and subsequently reduce the probability of obesity. In this study, the education variable will be proxied by the percentage of people in an MSOA with level 3 (A levels of equivalent) qualifications or higher.

Age

In a US study conducted amongst 24-38 year olds, Baum & Ruhm (2009) find a positive association between age and obesity, in which regression coefficients suggest a BMI increase of 0.119 kg/m^2 for each additional year lived. This relationship can be explained by both the 'in' and 'out' sides of the energy balance equation. Older people usually engage in less active lifestyles, whilst also experiencing reductions in metabolism and muscle mass. For this study, the age variable will be measured as the percentage of the total MSOA population that is over 65 years old.

II) IDENTIFYING THE POSSIBLE MEDIATORS OF THESE RELATIONSHIPS

The second part of this analysis focuses on exploring the factors that mediate the relationship between urban sprawl and obesity. For this assessment, the study will incorporate a relatively new method of mediation, conceptualized by Preacher & Hayes (2004). This was chosen as it comprises several well established processes, including the Baron & Kenny Causal Steps (1986) and Sobel Test (1982), whilst attempting to improve upon them by including a bootstrapping feature, involving the systematic resampling of 10,000 observations to relax the stringent assumptions on data distribution and normality.

This study explores 3 proposed mediators as demonstrated in Figure 1; weekly physical activity, commuting patterns and density of fast food outlets which are discussed in more depth below.

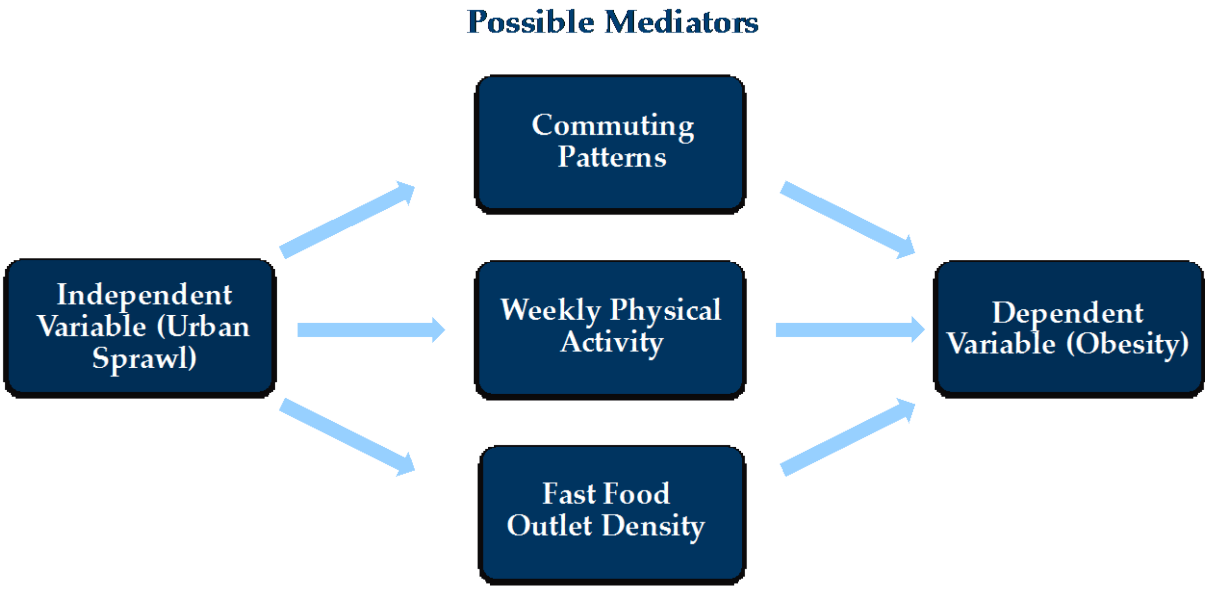

Figure 1: Mediation Model with 3 Possible Mediating Variables

Like the regression analysis, the dependent variable will be obesity- measured as the proportion of an MSOA which is clinically obese (BMI>30). The predictor variable will be a composite measure which attempts to portray a holistic view of urban sprawl. Consequently, the urban sprawl variable will comprise the four built environment factors used in the regression model (population density, public transport accessibility, street intersection density and land use mix). All four variables will be standardized and given a 25% weighting, producing a final figure of between 0-1, whereby 0 indicates no sprawl and 1 indicates total sprawl.

The following section will assess three possible factors that may play a role in mediating the relationship between urban sprawl and obesity prevalence within London.

Commuting Patterns

Crane (2000) postulates that sprawled residential environments often deter active methods of commuting, such as walking or cycling, but rather encourage high rates of car ownership due to the relatively large distances involved when accessing places of work. Consequently, this may lower levels of physical activity and contribute to greater rates of obesity. Frank et al. (2004) elucidate this notion empirically, in which they find that each extra kilometre walked per day reduces the likelihood of obesity. In this study, the proxy for commuting patterns was constructed as the percentage of people in each MSOA who commute to work by active methods of transport, which constitutes cycling and walking. It is hypothesized that this mediator variable will control the relationship as follows; when the level of urban sprawl falls, people engage in a greater level of active transport when commuting, thus elevating rates of physical activity and reducing overall obesity outcomes.

Weekly Physical Activity

The pathway from physical exercise to urban health is a complex one, especially within the context of built environments. Conventional wisdom within the public health sphere would suggest that sprawled locations offer a great deal of open green spaces. In theory, this could encourage physical activity in the form of leisurely walking trips, which may in turn reduce levels of obesity (Takano et al. 2002, Pretty et al. 2007). However, the New Urbanism school of thought would counter these claims by questioning the relationship between sprawl and accessibility to amenities which are designed to induce physical activity. Indeed, it has been argued that sprawled environments often lack sufficient sports facilities, including gyms and fitness centres, compared to more urbanised locations (Wendel-Vos et al. 2007). Moreover, De Bourdeaudhuij et al. (2003) reconcile this finding with obesity, by demonstrating a positive relationship between the availability of neighbourhood level sports/recreational facilities and levels of physical activity. Consequently, this study will hypothesize 'Weekly Physical Activity' to mediate the relationship between the independent and dependent variables as follows: with a rise in urban sprawl, the corresponding reduction in availability of sports/recreational facilities leads to a fall in physical activity, thus raising obesity outcomes.

FAST FOOD OUTLET DENSITY

Fraser et al. (2010) illustrates how the presence of fast food outlets has been strongly associated with a high prevalence of obesity, and further research has gone onto explore this link with respect to urban sprawl. Indeed, Schlosser (2012) argues that sprawled areas often have elevated densities of fast food and 'drive-thru' outlets due to the availability of cheap land required for on-site car parking. This may therefore act as a mediating variable, whereby greater urban sprawl could lead to greater fast food outlet density, thus promoting unhealthy eating and a rise in obesity outcomes. This indicator was computed with ArcGIS, using a similar method to the calculation of street intersection density.

PRELIMINARY ANALYSIS

As illustrated in Figures 3-7, the trends found within the maps seem to conform to the hypotheses set out in the previous section. High obesity rates (Figure 3) seem to be concentrated predominantly on the Eastern fringe of the city whilst lower rates are concentrated in the centre. This supports the idea that sprawl on the urban edge is associated with obesity, yet it could also be attributed to socioeconomic factors, particularly given that East London contains some of the the poorest neighbourhoods of the capital city. Shaded in green, the four built environment factors (Figures 4-7) are geographically distributed in an arrangement that is consistent with the associated literature. The central core of London contains all the principal features commonly associated with a large city such as high levels of population density, excellent public transport accessibility and high street intersection density. Conversely, these three variables all have considerably lower values around the periphery of London, which could imply that London's outer suburbs, while possibly not considered urban sprawl by absolute standards, share some characteristics Arguably therefore, the aforementioned maps help to identify the beginnings of an inverse association between the four urban sprawl variables and obesity outcomes across the capital city.

Obesity Prevalence

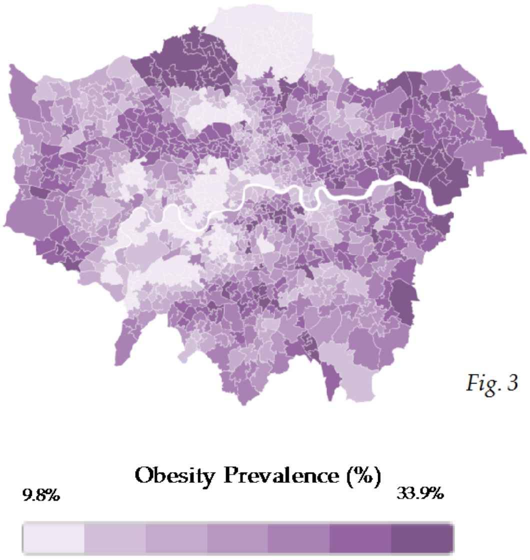

Fig. 3

Population Density

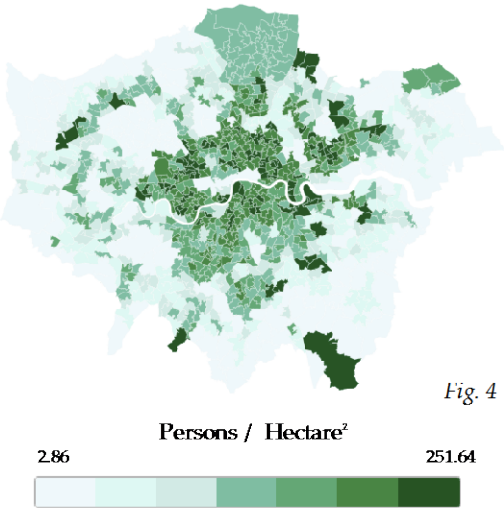

Fig. 4

Public Transport Accessibility

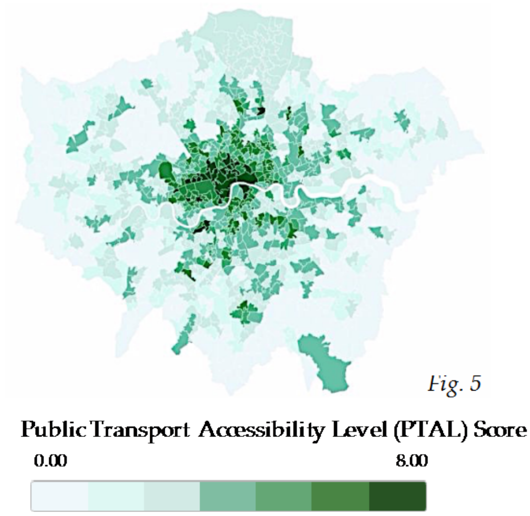

Fig. 5

Street Intersection Density

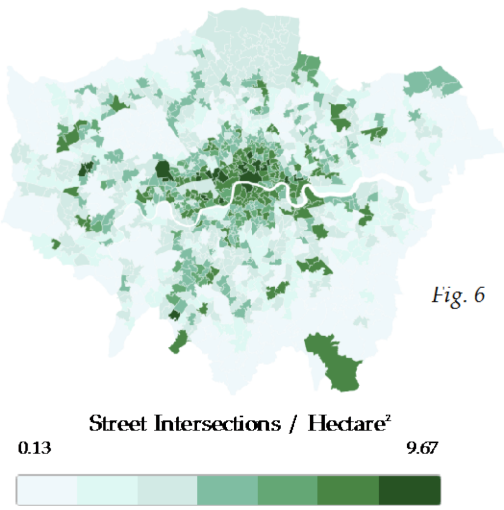

Fig. 6

Land Use Mix

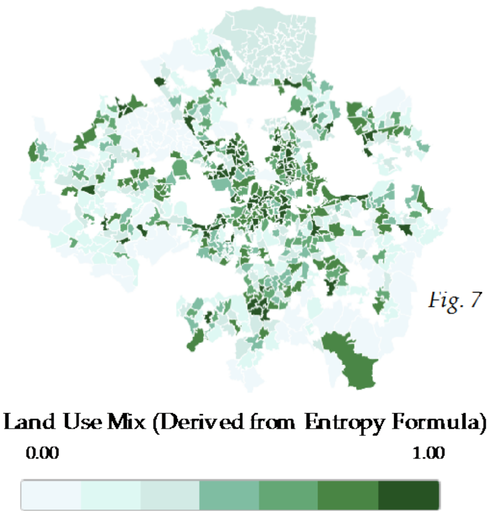

Fig. 7

REGRESSION ANALYSIS

The regression results hown in Table 2 confirm that the specified has a statistically significant predictive capability of the outcome variable, in this case obesity, explaining 53.4% of the overall variation in obesity rates across London.

Built Environment Factors

Population density was found to be negatively associated with obesity at a statistically significant level (p = .032), whereby a 1% rise in density corresponds to a fall in obesity prevalence by 0.076%. A similar relationship was established in the case of public transport accessibility (p = 0.46), in which a 1% increase leads to a 0.068% reduction in the dependent variable. Street intersection density was the third variable to be verified as statistically significant (p =.000). The model predicts that a 1% increase is linked to a 0.214% fall in obesity prevalence. Land use mix was the only built environment factor not to be statistically associated with obesity outcomes (p =.432).

Socioeconomic Factors

As hypothesized, the model estimates a statistically significant negative relationship between household income and obesity (p=.000). For a 1% rise in household income, there is a consequent decline in obesity prevalence of 0.262%. A positive association was unearthed for the unemployment variable (p= .000), whereby a 1% rise in the unemployment rate corresponds to a 0.278% increase in obesity prevalence. Indeed, a similar link was also found with the education variable (p=.000), in which a 1% increase in education levels (characterized by the percentage of an MSOA population with level 3 qualifications or above) is forecast to reduce obesity prevalence by 0.361%. Age was the sole socioeconomic variable not to be associated with obesity prevalence at a statistically significant level (p =.169).

Table 2

OLS Multiple Linear Regression Output

Model Output (Dependent variable: obesity rate)

Variables	Coefficients		T stat	Sig.
	Unstandardized	Standardized		
Built Environment Factors				
Population Density	-.009**	-.076	-2.143	.032
Street Intersection Density	-.008***	-.214	-8.576	.000
Public Transport Accessibility	-.003**	-.068	-1.801	.046
Land Use Mix	-.007	-.022	-.786	.432
Socioeconomic Factors				
Income	-.001***	-.262	-6.555	.000
Unemployment	.288***	.208	7.082	.000
Education	-.176***	-.361	-8.283	.000
Age	.060	.042	1.376	.169

ANOVA Test	F Value	Sig.
	118.109***	.000
Breusch-Pagan Test	Chi^2 Value	Sig.
	107.423	.942
R^2	.534	
Standard Error of The Estimate	.040	
N (Observations)	983	

Source: ONS Census 2011

* $p<0.10$

** $p<0.05$

*** $p<0.01$

Attribution of effects

By interpreting the standardized coefficients of the model, it was possible to directly compare the relative magnitude of the three significant built environment factors. The strongest built environment predictor variable in influencing obesity prevalence was street intersection density (-.214), followed by population density (-.076) and then finally the weakest variable, public transport accessibility (-.068). Moreover, it is interesting to note that education (-.361) and household income (-.262) were respectively the strongest and second strongest predictors of obesity out of all 8 independent variables entered into the model.

Upon further inspection of the results, it is also interesting to disaggregate the model into built environment versus socioeconomic effects. Table 3 reveals that built environment coefficients contribute to 30.3% of the model, whilst socioeconomic coefficients account for 69.7%. Consequently, whilst both categories contain three statistically significant variables, it can be concluded that socioeconomic factors are over twice as strong as built environment factors in explaining the model's predictions of obesity prevalence in London. This is consistent with a cross-sectional study of Atlanta, in which Bodea et al. (2009) also find that the built environment plays a significantly smaller role in shaping BMI outcomes when compared to the effects of socio-demographic influences.

Table 3

Attribution of effects

	Total Coefficients	Relative attribution to model
Built Environment Factors	.380	30.3%
Socioeconomic Factors	.873	69.7%
Total	1.253	100.0%

Source: ONS Census 2011

MEDIATION ANALYSIS

The results listed in Table 4 illustrate that the level of urban sprawl is indeed significant. Leading on from this is the examination of the direct effect, denoted by C Path, which is a measure of the relationship between urban sprawl and obesity when controlling for the three possible mediators. The results indicate that this effect is now no longer statistically significant ($p=0.138$), whilst the regression coefficient falls to 0.1564. Consequently, this change clarifies that at least one of the three proposed mediator variables must be significant in controlling the relationship between urban sprawl and obesity. It can be deduced that the three proposed mediators are responsible for controlling 63.4% of the effect of urban sprawl on obesity prevalence within London.

In order to gain further insight into the results, it is important to ascertain which specific mediators are statistically significant, as well as calculating their relative magnitudes. This can be calculated by first confirming if both the A Paths (the effect of urban sprawl on the mediator variable) and the B Paths (the effect of the mediator variable on obesity) are significant. Table 4 highlights that both A and B paths are significant for the commuting patterns and exercise per week factors, thus indicating that both of these variables are statistically responsible for mediating the relationship between urban sprawl and obesity. Contrastingly, the B Path in Fast Food Outlet Density has a P value of .9033, exemplifying how it cannot be classed as a significant mediator. It is possible to estimate the relative strength of the two significant mediators by evaluating their specific coefficients as a percentage of the total effect coefficient, or C Path (0.4323). Both commuting patterns and exercise per week have similar coefficients. Consequently, it can be deduced that the two aforementioned variables are each accountable for mediating roughly 32.0% of the relationship between urban sprawl and obesity across the capital city.

Table 4

Multiple Mediation Model Output

Path	Coefficient	Sig.
C Path (Total effect of urban sprawl on obesity)	.4323	.000***
C′ Path (Direct effect of urban sprawl on obesity after controlling for mediators)	.1564	.138
Difference in Coefficient (Overall indirect effect of mediators	.2759	
N (Observations)	983	

Mediator	A Path Coefficient (Effect of urban sprawl on mediator)		B Path Coefficient (Effect of mediator on obesity)		Mediator Sig.	Indirect Coefficient of Mediators	% of Relationship Controlled by Mediators
	Coefficient	Sig.	Coefficient	Sig.			
Weekly Physical Activity	-.1809	.000***	-.7644	.000***	✓	.1383	32.0%
Commuting patterns	-.6205	.000***	-.2232	.000***	✓	.1385	32.0%
Fast Food Outlet Density	-.0564	.000***	.0155	.9033	✖		

* *p*<0.10

** *p*<0.05

*** *p*<0.01

Source: ONS Census 2011

CONCLUSIONS

This paper set out to examine a possible nexus between obesity and urban land use patterns. The regression and mediation model results point to a strong association between London's neighbourhood-level physical characteristics and the resulting variation in obesity levels across the city. Indeed, population density, street intersection density and public transport accessibility are all statistically significant predictor variables. Overall, this cross-sectional study supports the notion that built environment factors do indeed influence the spatial distribution of obesity across London. Furthermore, the mediation analysis conducted in this paper indicates that physical activity and commuting patterns are the main built environment drivers of the relationship between London's built environment and obesity outcomes. However, socioeconomic factors are confirmed to be an overall more powerful predictor of neighbourhood-level obesity prevalence.

From a policy perspective, this paper would therefore support planning policies that counteract urban sprawl, particularly where synergies with other planning objectives such as reduced environmental impact, less strain on public finances and increased social cohesion are created. An important caveat is that redesigning existing neighbourhoods is expensive and may therefore not be feasible and cost-effective relative to other public health interventions that target weight loss more directly at the individual level.

It also important to stress that we observe large variations in obesity, diet and physical activity levels even within the same neighbourhoods, indicating that the impact of the built environment is far from deterministic and can thus be offset by individual attitudes and behaviours. However, it appears justified and supported by the majority of existing studies to conclude that appropriate planning policies can encourage healthy behaviours while accommodating sustainable development for a growing metropolis.

The use of MSOA data has enabled this study to explore the relationship between London's built environment and obesity outcomes across all 983 neighbourhood areas. Indeed, the aforementioned regression and mediation analysis have verified a set of interesting results which are largely in line with previous US findings. However, in the field of obesity-related research, criticism is often levelled at cross-sectional methodologies similar to the one implemented in this paper, due to non-random selection of residents into neighbourhoods (Zhao & Kaestner, 2010, Eid et al., 2008). Obese individuals may have a preference for residing in sprawled neighbourhoods (and non-obese in non-sprawled neighbourhoods), perhaps because of lifestyle choices and the ability to choose a main transport mode that is in line with a person's obesity status. In other words, an obese person may rule out neighbourhoods in their location choice that are not designed in a car-friendly manner and require extensive walking or using other non-car modes. While the dataset employed in this study does not allow us to test the self selection hypothesis directly, the issue of reverse causality may arguably be less prominent in the case of a single city (London), than that of the entire USA, as studied by Eid et al. (2008). Given the relatively small spatial remit of London, people are significantly more constrained in their locational choices, thus reducing the likelihood that residents will self-select into neighbourhoods based on their BMI. A further mitigating factor may be the fact that London has one of the highest housing costs in the world, making it more likely that the observed residential choices are driven by financial considerations and less by secondary concerns such as self-selection by body weight.

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