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Influence of the urban context on the relationship between neighbourhood deprivation and obesity

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Contributors

TF conceptualized the hypotheses and did the statistical analyses. JFV contributed to acquisition and interpretation of contextual data. JMO, HC and TF drafted the manuscript, and all authors were involved in subsequent drafts; MT and SH are guarantors for the NutriNet-santé study. All authors read and approved the final manuscript.

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Abstract

Background

In middle- and high-income countries, obesity is positively associated with neighbourhood deprivation. However, the moderating effect of the broader urban residential context on this relationship remains poorly understood.

Methods

In this study, we have examined the nonlinear and geographically varying relationship between neighbourhood deprivation and the likelihood of being a person with overweight among participants of the French NutriNet-Santé adult cohort study (n=68,698), adjusted for age, gender and educational level. Ten urban residential contexts (e.g., suburbs, peri-urban or rural areas) were defined. We used a multilevel generalised additive modelling framework for analyses.

Results

We found that the relationship between neighbourhood deprivation and overweight differed according to urban context, in terms of both linearity and intensity. Overall, the deprivation-overweight relationship was strongly positive (with a higher prevalence of overweight in deprived neighbourhoods) in suburban areas of Paris and of other large French cities, while weak or null in small towns and rural areas, and intermediate in inner cities. In addition, we observed in suburbs of Paris and in peri-urban belts of large cities that beyond a certain level of neighbourhood deprivation, the relationship with overweight plateaued.

Discussion

In a French population from a high-income country, suburbs, as well as moderately deprived neighbourhoods of peri-urban areas of large cities, are potential targets for public health and urban planning policies aiming at preventing obesity. Our results emphasize the value of local analyses to better capture the complexity and contextual variations of socioeconomic determinants of non-communicable diseases such as obesity.

Keywords: HGAM, multilevel model, obesity, local analyses, deprivation index, urban contexts

1. Introduction

Overweight and obesity have now reached pandemic levels. In 2016, 39% of adults aged 18 years and over were overweight (BMI ≥ 25 kg/m²) with 13% categorized as obese (BMI ≥ 30 kg/m²), representing 1.9 billion and 650 million persons, respectively (WHO, 2020). Notably, the prevalence of overweight and obesity have risen very rapidly, and globally, over the last 40 years (Swinburn et al., 2019). This trend is shaped by global drivers, including global markets and food systems, reflecting broad socioeconomic influences (Jaacks et al., 2019; Swinburn et al., 2011). In addition, there is spatial variation in BMI and obesity prevalence at different geographical scales, which remains poorly understood (Sarkar et al., 2017).

Such spatial patterning suggests that local moderating factors interact with global drivers to structure the actual complexity of obesity geography. Specifically, neighbourhood socioeconomic disadvantage or deprivation (Townsend, 1987) is a major local determinant of health (Kawachi and Berkman, 2003). In middle- and high-income countries, neighbourhood socioeconomic deprivation is positively associated with body mass index (BMI) and the prevalence of obesity (Harrington and Elliott, 2009; Lenthe and Mackenbach, 2002; Matheson et al., 2008). In addition, some studies highlighted variations in the relation between deprivation and obesity according to urbanicity levels (Ford and Dzewaltowski, 2011; Wang et al., 2013; Xu and Wang, 2015). Urbanicity is typically measured using an urbanisation ratio of population living in urban areas over the total population of a region or an administrative unit (e.g. county, department, etc.), with levels being established following the classic gradation of urban to rural, as found in the US and other censuses, and as adapted by different sectors, including health (Wang et al., 2013). While commonly used to characterise environmental contexts, urban-rural gradients fail to capture “how local areas or neighbourhoods affect health [and] how the broader spatial context within which neighbourhoods are situated may add to or modify the effects of local areas” (Diez Roux and Mair, 2010). For example, participants may be residing in different areas that are all classified as “urban” but have substantially different population densities, which could affect

the deprivation-obesity relationship. In addition, participants living in areas classified as “large metropolitan areas” may be located in the area of the primate city (e.g. Paris, London, New York) or in other large metropolitan areas (e.g. Marseilles, Birmingham, Boston), which suggests that a residential context at different levels of the urban hierarchy may also affect the deprivation-obesity relationship.

In the present study, we used a sample of 68,698 French adults to examine how the relationship between overweight and neighbourhood deprivation varies by residential context. Accordingly, a typology of residential contexts was established based on urbanicity, measured using multidimensional criteria and taking into account the hierarchy of cities in terms of socioeconomic and demographic importance.

2. Individual and contextual data

2.1. Study design and participants

Individual data regarding weight status and other individual covariates were collected from participants of the NutriNet-Santé study, an ongoing web-based cohort launched in France in May 2009, which focuses on relationships between nutrition and health (Hercberg et al., 2010). Volunteers aged 18 years or older living in France and having access to the Internet fill in self-administered web-based questionnaires at baseline, as well as at regular follow-ups using a dedicated, secure website. Moreover, the participants also completed a set of questionnaires assessing demographic and socioeconomic characteristics. In addition, residential addresses were obtained from all participants, geocoded to the parcel or street level and implemented as a shapefile in a geographical information system (GIS). Of the 83,128 participants with complete individual data for this study who have completed the questionnaires between 2009 and 2014, 14,075 participants were excluded due to missing data regarding their home addresses (n=12,991), residential related variables (n=355) or BMI (n=1,084). Therefore, the sample used in the present study included 68,698 participants.

Our study was conducted according to the guidelines laid down in the Declaration of Helsinki, and all procedures were approved by the Institutional Review Board of the French

Institute for Health and Medical Research (IRB Inserm #0000388FWA00005831) and the Commission Nationale Informatique et Libertés (CNIL #908450 and #909216). The study is registered at clinicaltrials.gov as NCT03335644. Electronic informed consent was obtained from each participant.

2.2. Weight status

At enrolment, participants were asked to report self-measurement of their weight and height using standardised procedures (while standing on a flat surface, lightly dressed and without shoes). In a validation study, we showed high level of agreement between anthropometric data obtained by self-report and standardised clinical measurements (Lassale et al., 2013).

Body mass index (BMI) was calculated as weight [kilograms] / height² [meters]. Obesity was defined according to World Health Organization standards as BMI \geq 30kg/m² and overweight (including obesity) as BMI \geq 25 kg/m² (WHO, 2000).

2.3. Individual covariates

Three sociodemographic variables were included in the models as covariates: age, sex and education (below high school diploma, high school diploma, and post-secondary graduate). These data were collected at baseline through self-administered questionnaires (Hercberg et al., 2010).

2.4. Neighbourhood deprivation index

We used the French deprivation index (FDep) as a measure of neighbourhood deprivation. This index was calculated following the protocol described by Rey and colleagues (Rey et al., 2009) and was already used and compared with other indices in a similar cohort (Temam et al., 2017). Deprivation has been initially defined by Townsend as a “state of observable and demonstrable disadvantage relative to the local community or the wider society to which an individual, family or group belongs” (Townsend, 1987). Empirically, in our study, deprivation

was quantified as the first component of principal component analysis, which included four aggregated socio-economic variables: median household income, percentage of high school graduates in the population aged 15 years and older, percentage of blue-collar workers in the active population, and unemployment rate. We used data provided by the National Institute of Statistics and Economic Studies (INSEE - <https://www.insee.fr/en/accueil>), the official authority collecting and disseminating information and statistics on French economics. The index was calculated at the smallest administrative unit for dissemination of French infra-municipal data, called IRIS. Typically, IRIS have a population of around 2,000 people and are thus similar to American census block groups. Each participant was assigned the value of his/her IRIS of residence.

2.5. Urban contexts

In this study, participants' neighbourhoods of residence were classified into 10 residential contexts, extending the two main classifications previously proposed by INSEE. The first one based on morphological and inhabitants' criteria (*urban unit* nomenclature: <https://www.insee.fr/en/metadonnees/definition/c1501>), and the other on functional criteria (*urban area* nomenclature: <https://www.insee.fr/en/metadonnees/definition/c2070>). Taken separately, these previous INSEE classifications have several limitations, as they do not distinguish the inner city from the suburbs of an urban centre. Moreover, they do not consider the Paris metropolitan area separately. Yet, in France, the Paris area represents an urban primacy, as it includes almost 20% of the French population and has a considerable economic influence (~30% of the national gross domestic product). We therefore designed a more comprehensive classification, combining demographic (number of inhabitants), morphological (built-up zone continuity) and functional (number of employed persons, commuting fluxes) thresholds, allowing our analysis to consider the hierarchy in the spectrum spanning from city centre, suburbs, and peri-urban to rural areas. The 10 resulting contexts are the following:

- (i) The inner city of Paris (intra-muros);
- (ii) Suburban municipalities of Paris, including municipalities composing the continuously built up Paris agglomeration, but excluding Paris;

- (iii) Peri-urban municipalities of Paris, including municipalities located in the Paris urban area and among which at least 40% of employed resident population work in Paris or in the municipalities attracted by Paris;
- (iv) Inner municipalities of large urban areas, including the most important municipality (inner city) of a large urban area. A large urban area is defined as a group of contiguous municipalities, including an urban central area providing at least 10,000 jobs;
- (v) Suburban municipalities of large urban areas, i.e. municipalities composing a large single build-up urban area, but excluding the inner city;
- (vi) Peri-urban municipalities of large urban areas, including municipalities among which at least 40% of employed resident population work in the urban centre or in the municipalities attracted by this centre;
- (vii) Municipalities of intermediate urban areas (defined as a group of contiguous municipalities including an urban central area providing from 5,000 to 10,000 jobs), whether inner cities, suburbs or peri-urban areas;
- (viii) Municipalities of small urban areas (defined as a group of contiguous municipalities, including an urban central area providing from 1,500 to 5,000 jobs), whether inner cities, suburbs or peri-urban areas;
- (ix) Multipolarized municipalities (MP);
- (x) Rural municipalities.

More details on the procedure leading to this classification, based on a local example illustrated by maps, are provided in supplementary materials.

3. Statistical modelling

First, a basic logistic model was computed to explore the overall relationship (i.e. without geographical variation) between overweight, deprivation and urban context. The logistic model was run with the dichotomized dependent variable (being a person with overweight or not), while adjusting for individual covariates (gender, age and education).

Then, to explore both nonlinearity and context-specific statistical relationships between deprivation and obesity, we used a hierarchical generalised additive modelling (HGAM) framework. This method combines two common methods into a single framework: hierarchical (or multilevel) models and generalised additive models (GAM) (Pedersen et al., 2019). Specifically, GAM is a method allowing statistical relationship between independent variables and the dependent one to be described by smooth curves, usually splines (Hastie and Tibshirani, 1990). This model is expressed as follows:

$$E(Y) = g^{-1}(\beta_0 + \sum_{j=1}^J f_j(x_j))$$

Where $E(Y)$ is the expected value of the response Y (with an appropriate distribution and link function g), f_j is a smooth function of the covariate x_j , β_0 is an intercept term, and g^{-1} is the inverse link function (Pedersen et al., 2019). The smooth function f_j is represented by a sum of K simpler, fixed basis functions ($b_{j,k}$) multiplied by corresponding coefficients ($\beta_{j,k}$), which need to be estimated:

$$f_j(x_j) = \sum_{k=1}^K \beta_{j,k} b_{j,k}(x_j)$$

These basic functions capture the complexity of each subsequent fitted curve. Too much complexity can lead to overfitting, i.e. to very erratic curves. To avoid such an overfitting and smooth the curves, a smoothing penalty is applied to basis function coefficients (Pedersen et al., 2019). This penalty affects the shape of the curves via a smoothing parameter that is selected using restricted maximum likelihood (REML). Typically, a smoothing parameter set to 0 leads to overfitting, while a very large value forces the curve to become a straight line. It is therefore a question of compromise between complexity and simplification of the studied statistical relationships. In this study, we used thin plate regression splines as a smooth function, as recommended for non-cyclic data (Wood, 2003). Besides the GAM, hierarchical or multilevel models are an extension of linear models accounting for the hierarchical – nested – structure of the data (Goldstein, 1987). Multilevel models specify models at a micro (e.g. individual) and at a macro (e.g. neighbourhood) level in a single framework. Accordingly, these models allow the consideration of context effects together with individual ones, avoiding both ecological and atomistic fallacies (Owen et al., 2016).

Moreover, in multilevel models, statistical relationships can vary by levels of the grouping variable (i.e. geographical contexts if this variable corresponds to spatial units) through random effects. The core idea of HGAMs is to combine GAM and multilevel models in order to allow varying nonlinear relationships for each level of grouping variable(s). In the present study, the grouping variable is the typology of urban contexts. More details about HGAM and the selection procedure of the final model are given in supplementary materials.

All statistical analyses were performed with R (R Development Core Team, 2018). The *mgcv* package (Wood, 2011) was used for computing HGAMs, following the codes created by Pederson and colleagues (Pedersen et al., 2019).

4. Results

4.1. Descriptive statistics

The 68,698 French adults study participants had a mean (sd) age of 44.2 (14.5) years, a high level of education (64% of participants having completed post-secondary school) and were mostly women (77%) (Table 2). In addition, they had a mean BMI of 24 kg/m² and 31.8% of them were overweight or obese. A total of 46% of the participants lived either in inner cities of large urban areas or in their suburbs. About 22% of the participants lived in the Paris area, including 5.7% in Paris *intra-muros*. The remaining individuals resided either in intermediate/small urban areas, or in multipolarized/rural units (Table 1).

*** *Insert Table 1 about here* ***

Table 2 shows mean BMI, overweight prevalence and the neighbourhood deprivation index summary statistics grouped by urban context. It can be observed that Paris and its suburbs, as well as large urban area inner cities and their suburbs, i.e. the most urbanised contexts, are those exhibiting the lowest BMI and overweight rates, in addition to the lowest deprivation indices on average. Moreover, the variability (standard deviation) of the

deprivation index is higher in cities and their suburbs compared to less densely populated areas.

**** Insert Table 2 about here ****

4.2. Results of global models

First, we computed the global generalised linear model to have an overview of average relationships over the entire sample. Specific types of urban context were included as a categorical explanatory variable, the reference category being suburbs of large urban areas.

The individual covariates were all associated with overweight, positively for age and negatively for gender (being a man is negatively associated with overweight) and education (< high school as reference category, see Figure 1). The deprivation index was also positively associated with the likelihood of being a person with overweight, meaning that the more deprived the neighbourhood, the higher the likelihood of being a person with overweight. Regarding urban contexts, residing in Paris intra-muros or in inner cities of large urban areas were negatively associated with the likelihood of being a person with overweight compared to residing in suburbs of large urban areas (reference category). In contrast, residing in the Paris suburbs, as well as in peri-urban or in multipolarized/rural areas was positively associated with the likelihood of being overweight. In other words, living in a highly urbanised context was associated with a lower likelihood of being a person with overweight, even after adjusting for individual covariates and neighbourhood deprivation. Estimates for other types of urban context (intermediate and small urban areas) were non-significant.

**** Insert Figure 1 about here ****

4.3. Results of hierarchical generalised additive models (HGAM)

GAM results are illustrated in Figure 2, in which relationships are plotted for each urban context. Regarding the overweight model, smooth coefficients are significant for five urban

contexts only: Paris and its suburbs, as well as all large urban areas (inner cities, suburbs and their peri-urban belt). There was no significant relation in less urbanised areas. In terms of wiggleness, most relationships had a linear shape, except in the peri-urban belt of large urban areas, where the statistical relationship was strong for the lowest values of deprivation only and tended to decrease in most deprived areas (Figure 2). Also, in Paris suburbs, the deprivation-obesity relationship was slightly stronger for the lowest values of the deprivation index and weaker for the highest values.

**** Insert Figure 2 about here ****

5. Discussion

In this study, we examined whether the relationship between neighbourhood deprivation and being a person with overweight varied in form and/or in intensity according to urban context among 68,698 French adults from the NutriNet-Santé cohort, while controlling for individual characteristics. Our main finding is that the deprivation-obesity relationship varied according to urban context. In general, our findings showed that this relationship was the strongest in suburbs of large cities (especially in the Paris area), the weakest in less urbanised contexts (small towns and rural areas), and intermediate in inner cities. This nonlinear scheme goes beyond similar studies in extending findings that were restricted only to low-income women (Ford and Dziewaltowski, 2011) or to geographical contexts which did not take into account the hierarchy between cities in a given urban system (Wang et al., 2013). Our results demonstrate the significance of the broader urban residential context, including its position in the urban system hierarchy. This key point supports the idea that within a general framework, public health policies should be adapted to local contexts for concrete application (Swinburn et al., 2019, 2011).

Some hypotheses can be proposed to explain the varying relationships between deprivation and overweight according to local residential contexts: (i) There are fewer contrasts in the least urbanised areas in terms of contextual deprivation, as indicated by the values of the deprivation index standard deviations in Table 2, while variability is at its maximum in suburban areas (especially in the suburbs of Paris). In general, social patterns in French cities

are different from those observed in U.S. cities, as deprived populations in France typically live in the suburbs rather than in inner cities. The renovation process of French suburbs is most often characterised by renewed attractiveness of working-class neighbourhoods, with incomers belonging to the upper middle class (Clerval, 2006), even if more complex socio-spatial processes are at play in some suburbs. Moreover, these neighbourhoods also increasingly gain population due to the pressure exerted by housing prices. Therefore, suburban areas – especially in Paris – are characterised by higher social heterogeneity compared to the inner-city, with a mixture of working-class, upper-middle class residents (Clerval, 2006). Such differentiated deprivation variability could also partly determine contrasts on relations in other local residential contexts. (ii) Furthermore, sizes of administrative units differed between local residential contexts, with increased size observed in the least urbanised areas, which could affect the deprivation-obesity relationship. As previously suggested by Ford and Dzewaltowski (Ford and Dzewaltowski, 2011), the influence of neighbourhood characteristics on individual behaviours diminishes with increased neighbourhood size.

We also found non-linear deprivation-obesity relationships within specific urban contexts. These relationships were linear in most residential contexts, but not in specific contexts such as the peri-urban belt of large urban areas and Paris suburbs. In these contexts, the relationship between deprivation and overweight was stronger for the lower half of the deprivation index values and plateaued beyond a certain threshold, towards most deprived neighbourhoods. These results would suggest that prevention policies should not only target the most deprived neighbourhoods, but also consider the entire social deprivation gradient. To address the needs of deprived populations at a local scale and promote equity in access to healthy lifestyle options in the local environment, public health practitioners should be aware of the influence of such geographic variation. This should help design programs that would identify at-risk populations within specific geographic contexts to better support policy development, provide increased resources and improve sustainability of interventions. It could be seen as a geographical approach of the “think global, act local” framework considering the food, transportation, land-use and urban-design systems that represent the major drivers of body weight gain and obesity (Swinburn et al., 2019).

In addition to the geographically varying relationships, our results showed an expected significant positive relationship between neighbourhood deprivation and risk of overweight, while adjusting for individual variables. Such neighbourhood inequality in overweight prevalence is in agreement with a number of previous studies in Europe (Maier et al., 2014), as well as in the US (Lovasi et al., 2009). Differences in access to neighbourhood facilities (e.g. food outlets with healthy options, sport facilities) have been hypothesised to be related to neighbourhood inequalities in dietary intake and physical activity, favouring weight gain and obesity (Lenthe and Mackenbach, 2002). In addition, neighbourhood differences in stressors (e.g. high traffic density, lower aesthetics and crime-related safety) may contribute to increases in unhealthy behaviors, such as sedentary lifestyle (Laraia et al., 2012). Further research should investigate the relationship of neighbourhood deprivation with dietary intake, physical activity and sedentary behavior according to urban context, using a similar approach as the one followed in the present paper.

One of the main strengths of our study is the use of hierarchical generalised additive modelling framework to unravel the spatial complexity of deprivation-overweight relationships. A number of previous studies have already applied the widespread GWR modelling approach for providing maps of local relationships between deprivation and obesity (see Oshan et al. (2019) for a review). However, this method fails to consider the hierarchy of cities in a given geographic context. Another potential approach is the use of the random slope multilevel model (Corsi et al., 2012); however, it does not allow exploring geographically varying nonlinear relations. Therefore, to overcome these limitations, the hierarchical generalised additive model used in the present study appears particularly suited to capture, simultaneously, spatial heterogeneity and nonlinearity of relationships.

It should be noted, however, that given the cross-sectional nature of this study, no causal pathway could be established between contextual deprivation and individual weight status. In addition, such pathways are mediated by both residential context and obesity-related behaviors, including food choices, availability and accessibility, which were not addressed here. Also, in terms of perspective, further works could explore the possibility of declining the deprivation index according to territorial context, in particular to better depict deprivation in rural settings. Even if the use of a single, standardized index makes comparison of statistical results between spatial contexts and between studies easier, an

ongoing debate still exists on the usability of "one-size-fits-all" deprivation indices comparing urban and rural area as they are often skewed (e.g. Burke and Jones, 2019). Finally, our sample included more women than in the general population, as well as more highly educated individuals, limiting the generalisability of our findings.

6. Conclusion

In conclusion, this work supports the notion that using a mean, smoothed view of statistical relationships may hide local mechanisms directly derived from specific spatial contexts, and, in turn, lead to partial or biased inferences (Feuillet et al., 2016, 2015). Our findings emphasise the importance of the local level for public health policies for preventing weight gain and obesity, taking into account the strong but varying deprivation-obesity relationship. Moreover, our results indicate that moderately deprived neighbourhoods, such as those of Paris suburbs and peri-urban parts of large cities, should not be neglected by public policies for tackling overweight and obesity. In exhibiting geographical heterogeneity of relationships, this study reinforces the contention that health-related ecological studies should consider local nuances – i.e. spatial heterogeneity – of statistical relationships to fully capture the variation of socioeconomic determinants of non-communicable diseases such as obesity.

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TABLES AND FIGURES

Table 1. Characteristics of the sample (n=68,698), NutriNet-Santé study.

Demographics	Mean or % (SD)
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Age (mean)	44.2 (14.5)
Gender (% women)	77.0
Education	
< high school (%)	2.8
High school (%)	33.2
Post-secondary school (%)	64.0
Weight status	
BMI (kg/m ²) (mean)	24.0
Overweight or obese (BMI > 25) (%)	31.8
Urban contexts	
Paris (%)	5.7
Paris suburbs (%)	14.2
Paris peri-urban areas (%)	2.7
Inner cities of large urban area (%)	24.1
Inner city suburbs of large urban area (%)	22.0
Peri-urban areas of large urban area (%)	15.6
Intermediate urban areas (%)	2.7
Small urban areas (%)	2.9
Multipolarized municipalities (%)	7.2
Rural municipalities (%)	2.8

Table 2. Descriptive statistics of weight status (BMI and percent of overweight including obesity) grouped by urban contexts.

Urban contexts	Individuals		BMI	Overweight (BMI \geq 25 kg/m ²)	Deprivation index*		
	N	%	mean (SD)	%	mean (SD)	Min (low deprivation)	Max (high deprivation)
Total sample	68,698	100	24.0 (4.6)	31.8	-0.3 (1.7)	-7.0	8.2
Paris intra-muros	3,938	5.7	22.9 (4.1)	21.9	-2.7 (1.7)	-6.8	2.5
Paris suburbs	9,783	14.2	23.9 (4.6)	31.6	-1.4 (1.9)	-7.0	4.4
Paris peri-urban areas	1,879	2.7	24.4 (4.8)	34.5	-0.7 (1.5)	-5.6	4.0
Inner cities of large urban area	16,540	23.9	23.5 (4.5)	28.0	-0.1 (1.8)	-4.8	7.3
Inner city suburbs of large urban area	15,112	21.9	24.1 (4.6)	32.9	-0.1 (1.3)	-5.1	8.2
Peri-urban areas of large urban area	10,693	15.5	24.2 (4.6)	34.6	0.2 (1.2)	-4.3	5.6
Intermediate urban areas	1,835	2.7	24.0 (4.5)	33.7	0.4 (1.1)	-3.9	5.0
Small urban areas	2,002	2.9	24.4 (4.8)	35.0	0.4 (1.1)	-3.3	6.4
Multipolarized municipalities	4,963	7.2	24.6 (4.9)	37.9	0.3 (1.1)	-4.4	5.3
Rural municipalities	1,953	2.8	24.7 (4.7)	38.9	0.5 (0.9)	-4.1	5.2

* z-scores: high scores indicate high deprivation

Figure 1. Associations between individual characteristics, urban contexts and deprivation index, and being a person with overweight (BMI \geq 25 kg/m²), estimated through a logistic model (n = 68,698). Coefficient estimates have been exponentiated (odds ratios).

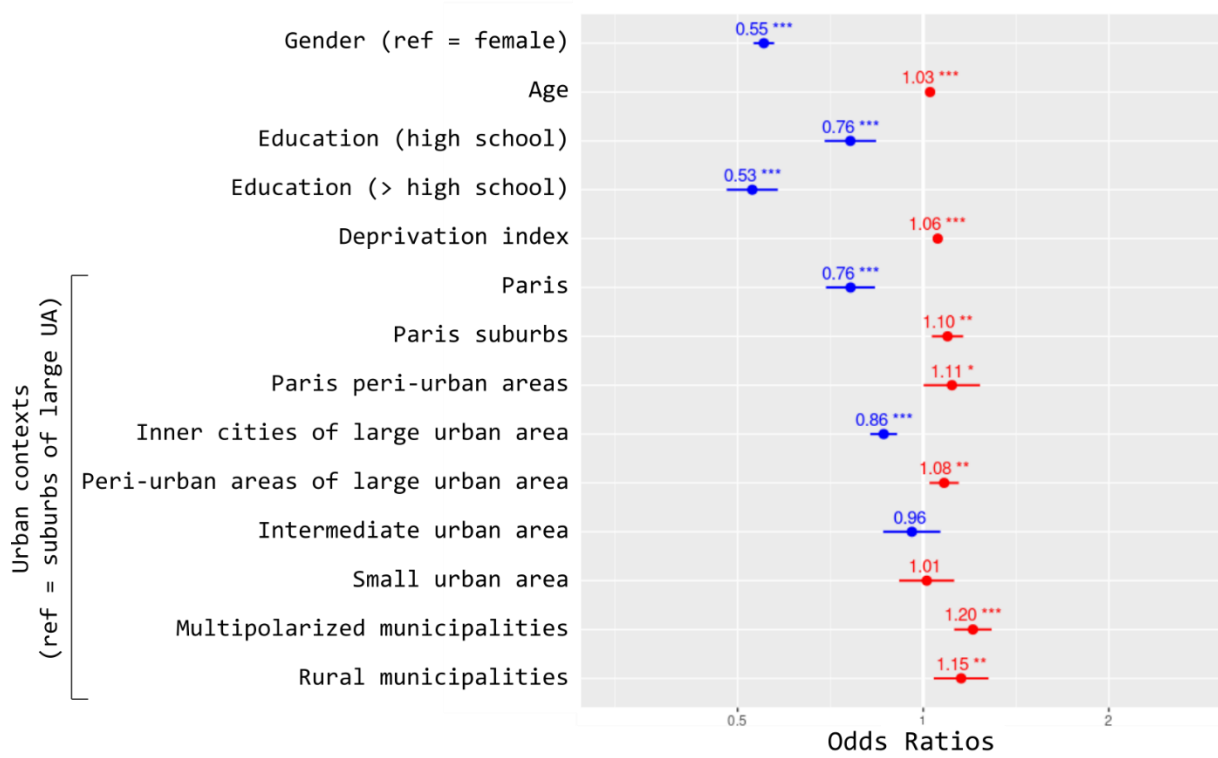
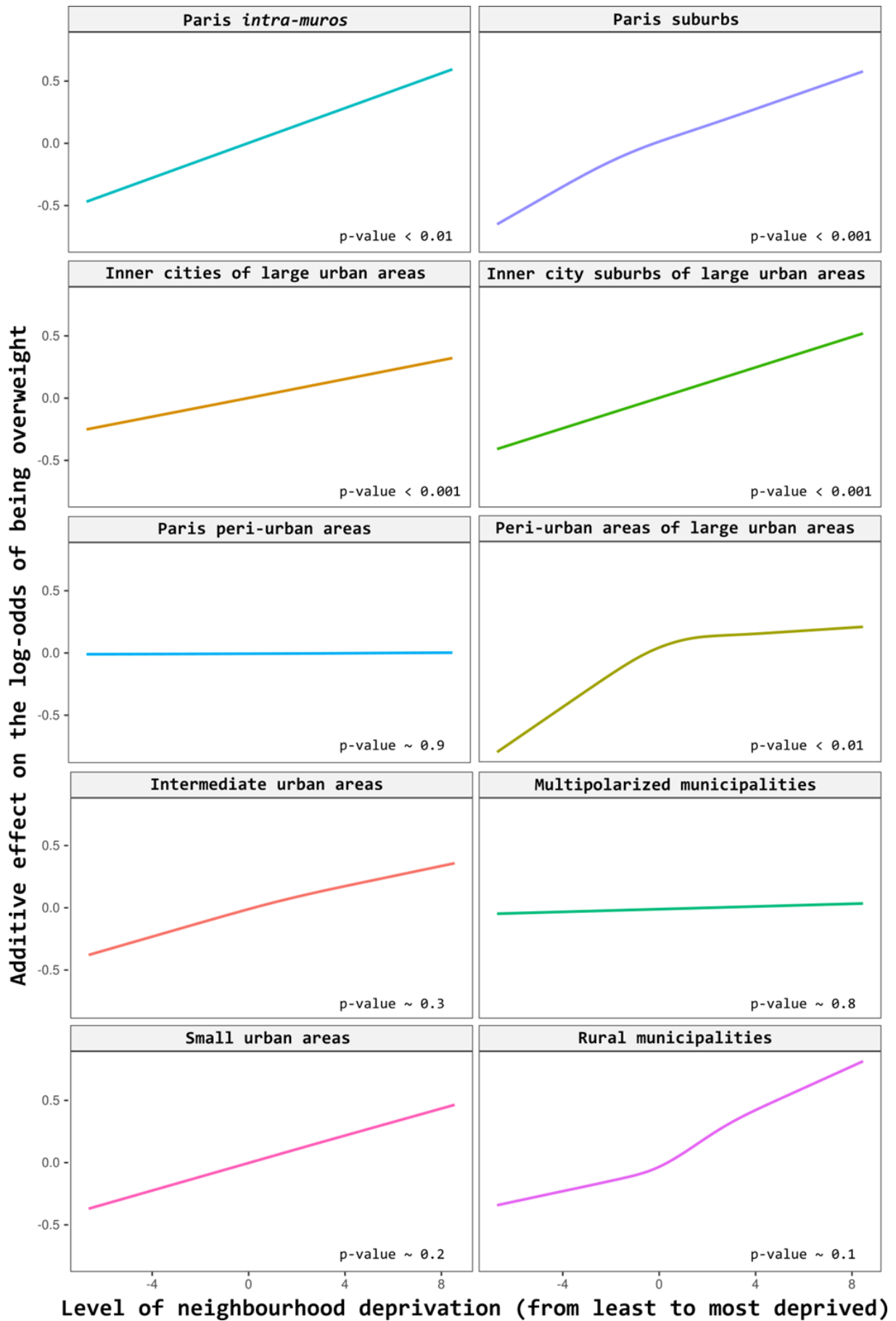


Figure 2. Plots of the smooth terms derived from the hierarchical generalized additive model, showing the shape of the relationships between BMI and neighbourhood deprivation index as a function of urban contexts. Estimates are adjusted for age, gender and education.



Highlights

- Spatial patterning in the deprivation-obesity relationship remains poorly understood
- Neighbourhood deprivation-overweight relations were studied in a large adult cohort
- The relationship was strongly positive in Paris suburbs and other large cities
- The relationship was weak or null in small/rural towns and medium in inner cities
- Moderately deprived neighbourhoods are potential targets for obesity prevention

CRedit author statement

TF conceptualized the hypotheses and did the statistical analyses. JFV contributed to acquisition and interpretation of contextual data. JMO, HC and TF drafted the manuscript, and all authors were involved in subsequent drafts; MT and SH are guarantors for the NutriNet-santé study. All authors read and approved the final manuscript.