Are Associations Between Neighborhood Socioeconomic Characteristics and Body Mass Index or Waist Circumference Based on Model Extrapolations?

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Background: We investigated whether neighborhood socioeconomic characteristics, measured within person-centered areas (ie, centered on individuals' residences) are associated with body mass index (BMI [kg/m^2]) and waist circumference. We used propensity-score matching as a diagnostic and validation tool to examine whether socio-spatial segregation (and related structural confounding) allowed us to estimate neighborhood socioeconomic effects adjusted for individual socioeconomic characteristics without excessive model extrapolations.

Methods: Using the RECORD (Residential Environment and CORonary heart Disease) Cohort Study, we conducted cross-sectional analyses of 7230 adults from the Paris region. We first estimated the relationships of 3 neighborhood socioeconomic indicators (education, income, real estate prices) with BMI and waist circumference using traditional multilevel regression models adjusted for individual covariates. Second, we examined whether these associations persisted when estimated among participants exchangeable based on their probability of living in low-socioeconomic-status neighborhoods (propensity-score matched samples).

Results: After adjustment for covariates, BMI/waist circumference increased with decreasing neighborhood socioeconomic status, especially with neighborhood education measured within 500-m radius buffers around residences; associations were stronger for women. With propensity-score matching techniques, there was some overlap in the odds of exposure between exposed and unexposed populations. As a function of socio-spatial segregation and an indicator of whether the data support inferences, sample size decreased by 17%–59% from the initial to the propensity-score matched samples. Propensity-score matched models confirmed relationships obtained from models in the entire sample.

Conclusions: Overall, adjusted associations between neighborhood socioeconomic variables and BMI/waist circumference were empirically estimable in the French context, without excessive model extrapolations, despite the extent of socio-spatial segregation.

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Previous research has documented that the prevalence of obesity is unequally distributed across neighborhoods and has identified neighborhood predictors, often related to the socioeconomic environment,[1–5] contributing to these inequalities after individual-level adjustment.[6] However, studies conducted to date have limitations related both to the measurement of neighborhood socioeconomic status and to the modeling of its associations with weight.

Regarding measurement, previous studies related to weight have measured neighborhood socioeconomic status in readily available administrative neighborhoods.[6] When census data geocoded at the building level are available, socioeconomic contexts assessed within "person-centered" neighborhoods (ie, centered on individuals' residences[8–11]) rather than in administrative neighborhoods probably better reflect the person's actual exposures to neighborhood characteristics. Moreover, person-centered neighborhoods more conveniently allow performing sensitivity analyses on the size[9] of the neighborhood on which associations operate.

When modeling associations with neighborhood socioeconomic status adjusted at the individual level, there is a large correlation between individual and neighborhood socioeconomic characteristics due to the social segregation of populations in space (concentration of low-socioeconomic-status populations in particular neighborhoods).[12] Consequently, some authors have suggested that there may not be sufficient overlap in the propensity of exposure to a low-socioeconomic-status neighborhood (estimated from individual socioeconomic characteristics) between residents from low- and high-socioeconomic-status neighborhoods to estimate adjusted neighborhood effects in typical studies of neighborhood and health.[13] Structural confounding refers to the fact that, due to the data structure determined by socio-spatial segregation, "the better one controls for the selection of persons to neighborhoods the less overlap there will be in the propensity for any subject to reside in any neighborhood other than their own."[14] A critical problem is that, even with this lack of data to estimate adjusted neighborhood effects, regression models provide estimates of neighborhood effects that are in fact based on excessive extrapolations, leading to "off-support" inferences.[14,15]

Following previous work,[13,16–18] we used propensity score matching to diagnose this problem, ie, to evaluate whether adjusted neighborhood effects are estimable, and are still observed when comparing exposed and unexposed participants who are exchangeable based on their propensity of exposure. Our aim was to evaluate whether structural confounding is a systematic threat to studies of neighborhood and health, as recently claimed.[12]

Overall, our goal was to address limitations related to the measurement of neighborhood socioeconomic exposures and the modeling of their associations with weight status and abdominal fat.

METHODS

Population

The RECORD Cohort Study (Residential Environment and CORonary heart Disease, www.record-study.org)[19–21] was used for the analyses. In 2007–2008, 7290 participants aged 30–79 years affiliated with the national health insurance system for salaried workers were recruited without a priori sampling during health checkups conducted by the Centre d'Investigations Préventives et Cliniques in the Paris metropolitan area. An eligibility criterion was residence in 10 of 20 administrative divisions of Paris or 111 other municipalities of the metropolitan area selected a priori. Eighty-three percent of the eligible participants at the health centers agreed to participate, completed the data collection, and were geocoded using their residential address. The French Data Protection Authority approved the study protocol. After excluding persons with missing values for body mass index (BMI)/waist circumference, the final samples available for analysis of BMI and waist circumference comprised 7230 and 7076 participants, respectively. Both samples included participants from 646 neighborhoods (TRIRIS geographic unit).

Individual Sociodemographic Variables

A range of personal sociodemographic characteristics were considered: age (divided in 3 classes); education (divided into 4 classes: no education, primary education and lower secondary education, higher secondary education and lower tertiary education, and upper tertiary education); mother's and father's education (divided into 3 classes: primary school or less, secondary school, and tertiary school); household income adjusted for household size (divided into 3 categories); and occupation (coded into 4 categories: high white-collar workers, intermediate occupations, low white-collar workers, and blue-collar workers). Five binary variables were determined: perceived financial strain, perceived job precariousness, presence of children in the household, whether vacations were taken over the previous year or not, and a proxy for attendance at cultural entertainments (theater, cinema, etc). We attributed to each person the Human Development Index of country of birth[22] as a crude proxy of cultural origin. A variable divided into 3 classes was used to distinguish people born in low, medium, and high-development countries.[23] Finally, 5 binary variables related to general values or attitudes toward health were considered: priority given to health, attitude toward prevention, propensity to keep healthy resolutions, and health-related external and internal locus of control (the belief that one's health depends on external forces such as God or fate, or alternatively on one's behavior).

BMI and Waist Circumference

Height (using a wall-mounted stadiometer) and weight (using calibrated scales) recorded by a nurse[24] allowed us to calculate BMI (kg/m^2).[25] Waist circumference was measured in cm using an inelastic tape placed midway between the lower ribs and iliac crests on the midaxillary line.[26]

Neighborhood Socioeconomic Variables

Administrative data sources geocoded at the building level allowed us to consider 3 neighborhood variables in various circular buffers around each participant's residence with a radius ranging from 100 to 10,000 m (proportion of residents aged >15 years with an upper tertiary education, from 2006 Population Census; median household income per consumption unit in 2006, from the General Directorate of Taxation; and mean value of dwellings sold in 2003–2007, from Paris-Notaries). These variables were divided into 4 categories comprising similar numbers of persons.

Statistical Analysis

To account for within-neighborhood correlation in BMI and waist circumference, we estimated multilevel linear regression models. Given sexual dimorphism in body habitus, all of the analyses were stratified by sex. The statistical analyses involved 4 steps.

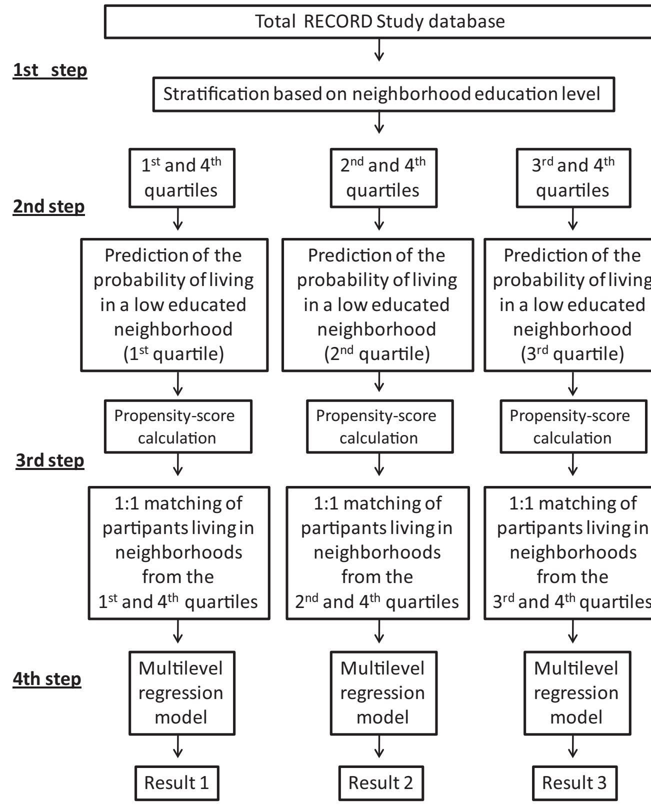
1. Based on models retaining only the individual variables associated with the outcomes in at least one of the models,

we estimated multilevel linear regression models containing the neighborhood variables measured in 500-m radius buffers (as commonly done in the literature[27–30]), either included separately or 2-by-2 into the models.

2. In a second step, we performed a sensitivity analysis for the spatial scale of the circular buffer to measure the neighborhood variable, to examine on which scale the associations operated. We ran 6 models with the neighborhood variable chosen in step one measured in 100–10,000-m radius circular buffers.

The aim of these 2 exploratory steps was to select the best neighborhood socioeconomic marker of high weight status and abdominal fat, based on the hypothesis that the neighborhood socioeconomic variable and the spatial scale for which the association is the strongest and model fit the best are the ones that most accurately capture the effects at play. We assessed model goodness-of-fit adjusted for model complexity with the Akaike information criterion.[31]

3. In the third step, we conducted the propensity score matching analyses, using the neighborhood socioeconomic variable and spatial scale chosen in the previous steps. As detailed in Figure 1, to re-estimate the "effect" of the neighborhood variable divided into quartiles, we defined 3 separate samples comprising participants: (i) from the first and fourth neighborhood socioeconomic quartiles, (ii) from the second and fourth socioeconomic quartiles, and (iii) from the third and fourth socioeconomic quartiles. For each of these 3 samples of participants, we estimated the propensity score for "living in a neighborhood with a lower socioeconomic status," modeling with a traditional logistic regression the odds of living in the lower quartile of neighborhood socioeconomic status (first quartile in the first sample, second quartile in the second sample, and third quartile in the third sample), as a function of all individual variables (i) that were initially hypothesized to affect BMI and waist circumference and (ii) that were hypothesized to possibly influence place of residence.[32–34] We adjusted for health-related values because such values are connected to other general life values that might influence residential strategies. Separately in these 3 cases, we matched each participant living in neighborhoods with high socioeconomic status (fourth quartile) with a participant living in neighborhoods with lower socioeconomic status (first, second, and third quartiles, respectively) who was randomly selected among the participants with a comparable propensity score. We set the caliper at ±0.05 (range of acceptability for matching on the probability scale), and matched participants 1:1 until it was no longer possible to match; this resulted in 3 samples of matched participants that were smaller than the 3 samples from the beginning of step 3 (details are provided in Fig. 1). We were particularly interested in the extent to which sample size decreased after matching, as related to the magnitude of social segregation in space, and as an indicator of the extent to which adjusted neighborhood effects are estimable in our study territory.



Results reported in Table 3

Neighborhood education level	
High	Reference
Medium-high	Result 3
Medium-low	Result 2
Low	Result 1

FIGURE 1. Summary of the analyses using the propensity-score (PS) matching technique.

4. In the fourth step, we estimated differences in BMI and waist circumference between participants from neighborhoods with a high and a lower socioeconomic status, rerunning the same model as in the first step, but applied to the 3 reduced propensity-score matched samples. As propensity-score matching is a form of inexact matching that matches on a score rather than on the covariates themselves,[33] and because analyses were not conducted within matched pairs, the models in the propensity-score matched samples were adjusted for individual socioeconomic characteristics to address remaining imbalance in covariates between exposure groups.

All the analyses were conducted using SAS 9.2 (Cary, NC).

RESULTS

Descriptive information on study participants is presented in Table 1. In models adjusted for age and sex, intraneighborhood correlations were 0.05 and 0.03 for BMI and waist circumference, respectively (eAppendix 1, http://links.lww.com/EDE/A494). In models adjusted for individual covariates, higher BMI and waist circumference were observed for women (but not men) born in low development countries, with a low education level, with a low white-collar occupation, and for those reporting financial difficulties. Furthermore, among both men and women, BMI and waist circumference were higher for participants who did not practice cultural entertainments and for those who expressed a health-related external locus of control. Moreover, BMI and waist circumference were lower for men and women who expressed a propensity to keep healthy resolutions (Table 2).

Using multilevel models applied to the entire sample including each neighborhood variable separately (500-m radius buffers), living in neighborhoods with lower income, lower real estate prices, and particularly lower education level were associated in a dose-response pattern with higher BMIs and waist circumferences, after adjustment (Table 3, full models in eAppendix 2, http://links.lww.com/EDE/A494). We selected neighborhood education for the next steps of the analyses, based on the following 3 reasons: (i) neighborhood education was more strongly associated with the outcomes than neighborhood income or real estate prices; (ii) neighborhood education led to a better fit to the data than the other neighborhood variables; and (iii) only neighborhood education remained negatively associated with the outcomes when neighborhood variables were introduced 2-by-2 into the models.

In models estimated with an interaction term between sex and neighborhood education, as well as models stratified by sex, the associations between neighborhood education and BMI and waist circumference were stronger among women.

Regarding the buffer spatial scales, sensitivity analyses indicated that the point estimates for the relationships between neighborhood education and BMI and waist circumference slightly increased with the radius of the area from 100 to 500 m, and then decreased from 500 to 10,000 m, particularly among women (Fig. 2). The lowest Akaike information criterion was observed when using 500-m radius buffers (with more important differences among women), supporting the selection of this neighborhood spatial scale for the further analyses.

Logistic models estimated for the odds of living in low educated neighborhoods (to construct propensity score) suggest, for both men and women, that having a low individual education and parents with a low education, being born in a low development country, having a low income, and having a low social class occupation were associated with increased odds of living in low-educated neighborhoods. Furthermore, among men, reporting no vacations and no cultural entertainments, as well as giving a high priority to health, were also

TABLE 1. Descriptive Information[a] on the RECORD Participants Stratified by Sex, Paris Metropolitan Area, 2007–2008[b]

Variables	Men (n = 4738)	Women (n = 2496)
BMI (kg/m^2); mean (range)	26 (15.6–46.0)	25 (14.3–53.7)
Waist circumference (cm); mean (range)	89 (48.0–148.0)	78 (50.0–132.0)
Age (years)		
30–44	36	33
45–59	43	39
60–79	20	28
Human development index of country of birth		
Low	5	5
Medium	16	16
France	72	68
High (other than France)	8	12
Individual education		
Low	7	9
Medium-low	23	28
Medium-high	27	34
High	43	29
Mother's education		
Low	44	49
Medium	40	37
High	16	13
Father's education		
Low	35	39
Medium	33	31
High	31	27
Household income		
Low	24	29
Medium	40	42
High	36	28
Occupation		
Blue-collar	14	6
Low white-collar	31	53
Intermediate	6	5
High white-collar	43	25
Perceived job precariousness	18	18
Perceived financial strain	14	20
No vacation in the past year	16	20
Low practice of cultural entertainments	22	25
Health-related external locus of control	20	23
Health-related internal locus of control	92	87
Propensity to keep healthy resolutions	78	79
Attitude towards prevention	77	83
High priority given to health	87	91
Presence of children in the household	31	24

[a]% except where otherwise indicated.
[b]Descriptive statistics were computed in a sample excluding participants with missing values both for BMI and waist circumference.

TABLE 2. Associations for BMI and Waist Circumference From Regression Models Adjusted for Individual and Maternal Variables Stratified by Sex, Paris Metropolitan Area, 2007–2008

	Men		Women	
Variables	BMI (kg/m^2) β^a (95% CI)	Waist Circumference (cm) β^a (95% CI)	BMI (kg/m^2) β^a (95% CI)	Waist Circumference (cm) β^a (95% CI)
Human development index of country of birth				
High[b]	0.00	0.00	0.00	0.00
Medium	0.12 (−0.40 to 0.63)	0.20 (−0.68 to 1.08)	0.63 (0.09 to 1.17)	0.61 (−0.67 to 1.88)
Low	0.22 (−0.08 to 0.52)	−1.48 (−2.97 to 0.02)	2.41 (1.49 to 3.33)	5.08 (2.92 to 7.23)
Individual education				
High[b]	0.00	0.00	0.00	0.00
Medium-high	0.46 (0.19 to 0.72)	0.73 (−0.05 to 1.51)	0.17 (−0.32 to 0.66)	0.11 (−1.06 to 1.28)
Medium-low	0.88 (0.57 to 1.20)	1.96 (1.04 to 2.89)	1.36 (0.81 to 1.91)	2.65 (1.33 to 3.97)
Low	0.43 (−0.05 to 0.90)	0.41 (−0.99 to 1.82)	2.69 (1.89 to 3.49)	4.93 (3.02 to 6.84)
Occupation				
High white-collar[b]	0.00	0.00	0.00	0.00
Intermediate	−0.20 (−0.66 to 0.26)	−1.02 (−2.38 to 0.33)	0.40 (−0.50 to 1.30)	0.25 (−1.92 to 2.42)
Low white-collar	−0.27 (−0.54 to 0.01)	−0.93 (−1.72 to −0.14)	0.50 (0.02 to 1.00)	1.40 (0.23 to 2.56)
Blue-collar	−0.49 (−0.88 to −0.10)	−1.89 (−3.03 to −0.74)	−0.14 (−1.10 to 0.82)	−0.29 (−2.57 to 1.98)
Perceived financial strain (vs. not[b])	0.25 (−0.07 to 0.56)	0.70 (−0.22 to 1.63)	0.52 (0.02 to 1.02)	1.34 (0.16 to 2.52)
Low practice of cultural entertainments (vs. high[b])	0.41 (0.12 to 0.70)	1.66 (0.82 to 2.50)	1.27 (0.78 to 1.77)	3.10 (1.91 to 4.29)
Health-related external locus of control (vs. not[b])	0.32 (0.04 to 0.60)	1.11 (0.29 to 1.94)	0.86 (0.38 to 1.35)	2.26 (1.10 to 3.42)
Propensity to keep healthy resolutions (vs. not[b])	−1.04 (−1.31 to −0.77)	−3.60 (−4.39 to −2.80)	−1.84 (−2.32 to −1.35)	−4.60 (−5.76 to −3.45)

Models were adjusted for all the variables reported in the table, age and the examination center.
[a]The regression coefficients β are expressed in kg/m^2 in the model for BMI and in cm in the model for waist circumference.
[b]Reference category.

associated with increased odds of living in low-educated neighborhoods. In the opposite direction, perceived precariousness was associated with decreased odds of living in low-educated neighborhoods (full models in eAppendix 3, http://links.lww.com/EDE/A494).

In Figure 3, the probability (propensity score, according to individual characteristics) of living in a neighborhood with a lower education level is plotted for the RECORD participants who lived in high and in lower educated neighborhoods using the BMI sample, similar results were obtained for waist circumference. As expected, based on their individual characteristics, residents from neighborhoods with a lower education had higher probabilities of living in lower educated neighborhoods, and residents from high educated neighborhoods had lower probabilities of living in neighborhoods with lower education levels. Comparing the top, middle, and bottom parts of Figure 3 (in which residents from the fourth quartile of neighborhood education were successively represented with residents from the first, second, and third quartiles of education), we observe that the overlap between the curves increases when comparing neighborhood education categories that are closer to each other (see Fig. 3 legend).

The propensity score matched sample for the first and fourth neighborhood education quartiles was, for example, 57% smaller (n = 1026) than the original sample (n = 2368) in the analysis for BMI among men, and 59% smaller (n = 516) than the original sample (n = 1246) among women (Table 4). The decrease in sample size was less important when we compared closer neighborhood education categories, ie, the second and fourth quartiles (sample size was reduced by around 33% for BMI and waist circumference), and the third and fourth quartiles (around 17% smaller sample sizes were observed).

Estimating models in the propensity score matched samples, we obtained point estimates that were largely comparable to those from models based on the entire sample: residents from low-educated neighborhoods had an increased BMI and waist circumference (Table 5, full models in eAppendix 4, http://links.lww.com/EDE/A494). As shown in the Table, a notable difference between the 2 approaches was that the 95% confidence intervals (CIs) were wider when based on the propensity-score matched samples, as a result of their smaller size (descriptive information on matched and not-matched samples in eAppendix 5, http://links.lww.com/EDE/A494).

DISCUSSION

We observed that living in low socioeconomic status neighborhoods was associated with an increased BMI and waist circumference even after adjustment for individual and maternal characteristics. Although a considerable number of studies investigated relationships between area socioeco-

TABLE 3. Associations Between Neighborhood Socioeconomic Status and BMI or Waist Circumference From Regression Models Estimated Separately for Each Neighborhood Variable (500 m Radius Buffers for the Neighborhood Variables), Stratified by Sex, Paris Metropolitan Area, 2007–2008

	Men		Women	
Variables	**BMI (kg/m²) β[a] (95% CI)**	**Waist Circumference (cm) β[a] (95% CI)**	**BMI (kg/m²) β[a] (95% CI)**	**Waist Circumference (cm) β[a] (95% CI)**
Neighborhood education level[b]				
Fourth quartile (high)[c]	0.00	0.00	0.00	0.00
Third quartile (medium-high)	0.18 (−0.12 to 0.48)	0.14 (−0.72 to 1.01)	0.12 (−0.39 to 0.63)	0.24 (−0.97 to 1.46)
Second quartile (medium-low)	0.35 (0.04 to 0.65)	0.59 (−0.29 to 1.47)	0.42 (−0.11 to 0.95)	0.70 (−0.55 to 1.95)
First quartile (low)	1.01 (0.68 to 1.34)	2.22 (1.26 to 3.18)	1.79 (1.21 to 2.38)	3.96 (2.57 to 5.35)
Neighborhood real estate prices[d]				
Fourth quartile (high)[c]	0.00	0.00	0.00	0.00
Third quartile (medium-high)	−0.02 (−0.32 to 0.28)	−0.03 (−0.91 to 0.84)	0.10 (−0.42 to 0.62)	−0.002 (−1.23 to 1.22)
Second quartile (medium-low)	0.07 (−0.24 to 0.38)	0.24 (−0.66 to 1.13)	0.51 (−0.02 to 1.04)	1.33 (0.09 to 2.57)
First quartile (low)	0.34 (0.01 to 0.67)	0.29 (−0.66 to 1.24)	0.85 (0.29 to 1.40)	1.89 (0.59 to 3.20)
Neighborhood median income[e]				
Fourth quartile (high)[c]	0.00	0.00	0.00	0.00
Third quartile (medium-high)	0.10 (−0.21 to 0.40)	−0.31 (−1.19 to 0.57)	0.02 (−0.50 to 0.54)	0.08 (−1.14 to 1.30)
Second quartile (medium-low)	0.28 (−0.03 to 0.60)	0.19 (−0.71 to 1.09)	0.48 (−0.05 to 1.01)	1.22 (−0.02 to 2.47)
First quartile (low)	0.42 (0.09 to 0.76)	0.49 (−0.48 to 1.46)	1.48 (0.91 to 2.05)	3.07 (1.73 to 4.43)

Models were adjusted for age, examination center, Human Development Index of the country of birth, individual education level, occupation, perceived financial strain, low practice of cultural entertainments, health-related external locus of control, and propensity to keep healthy resolutions.

[a]The regression coefficients β are expressed in kg/m² in the model for BMI and in cm in the model for waist circumference.

[b]Neighborhood education level (proportion of residents aged >15 years with an upper tertiary education, value from 0 to 1), mean: 0.4, range: 0.1–0.7 for the BMI and waist circumference samples.

[c]Reference category.

[d]Neighborhood real estate prices (rank of the mean value of dwellings sold, value from 1 to 1000), mean: 425.2, range: 25.7–933.3, in the BMI sample, and mean: 423.9, range: 25.7–933.3, in the waist circumference sample.

[e]Neighborhood median income per consumption unit in Euros, mean: 22,641.3, range 8857.8–45,814.8, in the BMI sample, and mean: 22,590.4, range: 8857.8–45,814.8, in the waist circumference sample.

nomic characteristics and BMI and waist circumference,[6] none of these studies implemented any of the following methodological improvements: (i) the measurement of neighborhood socioeconomic status in person-centered areas based on building-level data and the investigation of the optimal spatial scale of measurement of neighborhood variables; and (ii) the comparison between multilevel analyses performed with the entire sample and with restricted propensity score matched samples to assess the exchangeability of exposed and unexposed participants. These 2 aspects are largely complementary because they are related to the measurement of neighborhood socioeconomic status and the modeling of its associations with weight.

Strengths and Limitations

Regarding study strengths, very few other studies[9,11] have elaborated neighborhood socioeconomic variables in person-centered areas defined on various spatial scales using administrative sources geocoded at the building level, and none of them in relation to weight. This approach in our study probably contributed to reducing exposure misclassification biases. Regarding health data, as noted in our recent review,[6] few neighborhood studies considered indicators of central adiposity as we did.

Regarding study limitations, first, even if our sample is not strictly representative of the Paris Metropolitan area,[20] we selected a priori a panel of municipalities from the region to ensure the presence in the sample of people from all socioeconomic backgrounds. Second, the present study considered only participants' current residential neighborhood, disregarding socioeconomic status of previous residential neighborhoods. Third, regarding the analyses, we did not assess whether increases in BMI and waist circumference with decreasing neighborhood education were of different magnitudes at different quantiles of these continuous anthropometric variables. Using quantile regression, eAppendix 6 (http://links.lww.com/EDE/A494) shows that these associations were larger at higher levels of BMI/waist circumference.

New Methodological Insight

The influence of residential neighborhood delimitations on the associations between neighborhood characteristics and health is an important issue that is often neglected. Most researchers do not conduct sensitivity analyses for the spatial scale of measurement of neighborhood characteristics, and when a sensitivity analysis is performed, it is generally not reported. For example, Auchincloss and colleagues[35] used kernel-density techniques to smooth census-block group (rather than building level) data to determine variables within circular areas, but they did not perform any sensitivity analysis of the spatial scale of measurement. Mason and col-

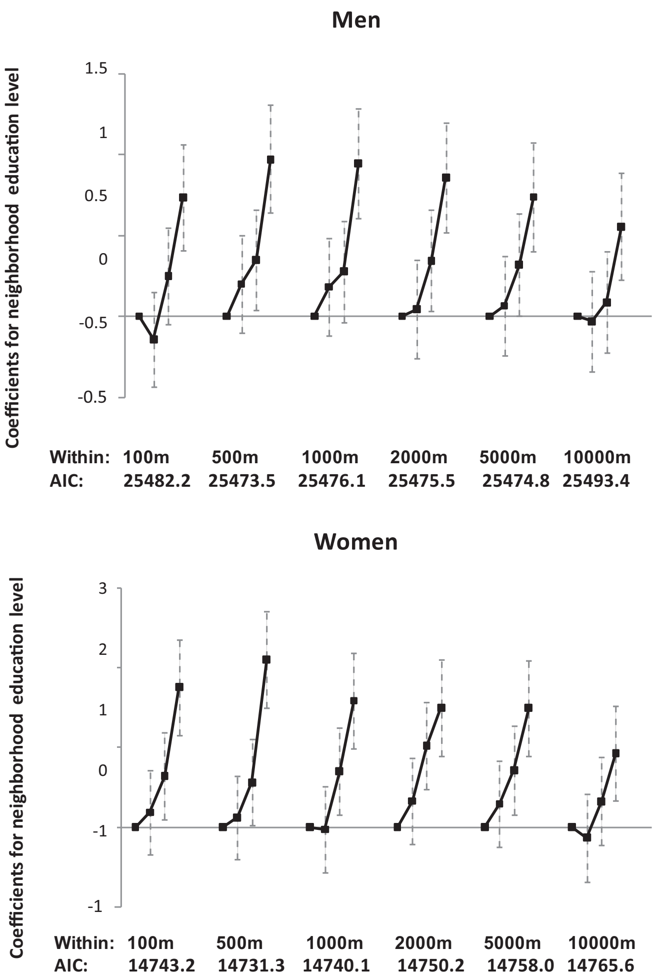


FIGURE 2. Adjusted differences in BMI (kg/m^2) according to neighborhood education level obtained from regression models adjusted for individual sociodemographic characteristics using different circular buffers for the neighborhood education variable with radiuses from 100 to 10,000 m. Each Akaike information criterion (AIC) presented on the figure corresponds to a separate model in which neighborhood education was measured on a particular spatial scale. Similar patterns of association were observed for waist circumference.

leagues[36] conducted but did not report a sensitivity analysis on the spatial scale of neighborhood factors, but their neighborhood measures were based on census tract data rather than on building-level census data as reported in this article.

The choice of the buffer scale may be based on 2 criteria: (1) plausible social and biologic hypotheses of environmental health influences (if there are a priori hypotheses on the spatial scale to retain) and (2) explicit exploratory comparison of the different spatial scales. The choice of a 500-m buffer scale in our analyses was a consequence of these 2 aspects. We assumed a priori that environmental conditions may be associated with health when factors are measured in "walkable" areas from the residence. Areas larger than 500-m radius buffers may not be easily "walkable," particularly for many of the aged participants of our sample. At the other extreme, smaller geographic areas (eg, with a 100-m radius) may be too small to represent "walkable" areas, therefore leading to weaker associations with weight. This hypothesis of exposure within "walkable" areas may explain why the empirical associations with weight or with abdominal fat were weaker when neighborhood education was measured within areas that were either too small or too large (in areas with a radius below or above 500 m in our case). However, the choice of spatial scale should be made carefully, rerunning sensitivity analyses in each specific study area, for each specific contextual factor and each outcome.

As a second methodological innovation, we used propensity score matching to perform analyses among participants who are exchangeable between neighborhood exposure groups on the basis of a number of individual sociodemographic characteristics that influence the likelihood of exposure to a low socioeconomic status environment. Propensity-score matching was not used in itself as an alternative to adjustment. In the literature, propensity-score matching is typically employed to reduce model dependence, and to estimate associations in a more empirical way than what would be necessary without matching.[33] In line with this practice, propensity-score matching was employed as a diagnostic tool to identify potential situations of structural confounding, and as a validation tool to verify that the adjusted neighborhood effects of interest can be estimated without excessive model extrapolations, ie, with a reasonable amount of data in the various cells of the cross-tabulation between explanatory variables ("on-support" inferences).[12–13]

There was considerable socio-spatial segregation in our sample, because sample size for estimating the effect of the first versus the fourth quartile of neighborhood education on BMI and waist circumference was halved when we applied propensity-score matching. However, matching exposed and unexposed study participants by their propensity score to live in a low-educated neighborhood showed that, in our French sample, there was some overlap in propensity score between them (which might not be the case in other countries, eg, in certain US territories).[12] Therefore, to measure this overlap, quantify the socio-spatial segregation level, and compare it across studies, we recommend explicitly presenting the percentage of reduction in sample size (as in Table 4) when undertaking propensity-score matching. This may help to reach the more balanced conclusion that structural confounding is perhaps not a systematic threat to studies of neighborhood and health, as recently claimed.[12] Furthermore, it is difficult to provide a definite cutoff for the percentage reduction in sample size beyond which it would seem unreasonable to estimate the adjusted neighborhood effect; the percentage reduction in sample size with matching is somewhat dependent on the caliper size selected for matching.

In terms of point estimates, we found a striking similarity between those obtained using the entire sample and those derived from the restricted propensity-score matched

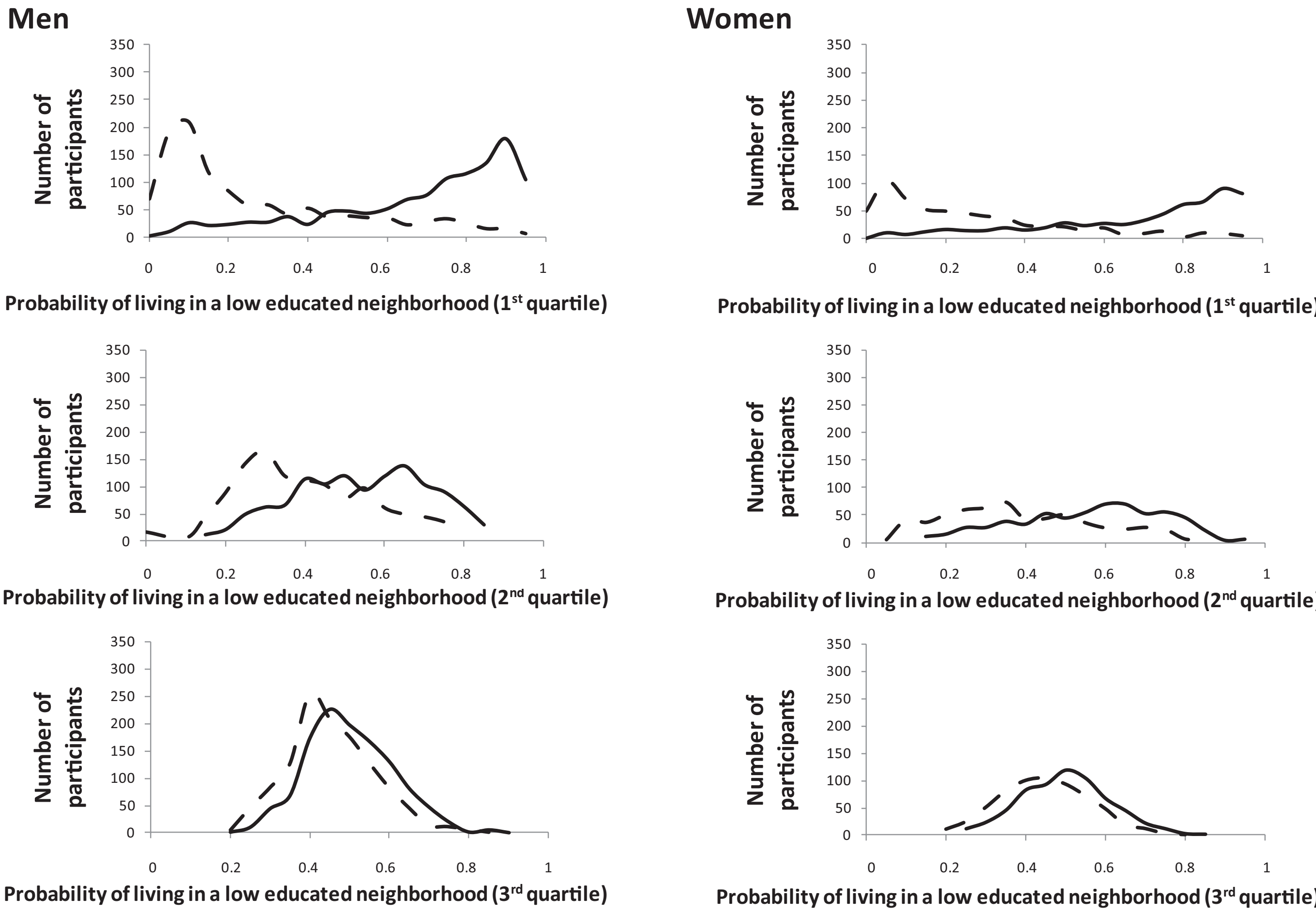


FIGURE 3. Distribution of the propensity-score for living in a neighborhood with a lower education level provided separately for participants residing in lower and high educated neighborhoods (BMI sample, stratified by sex). Solid lines represent residents from high educated neighborhoods and dashed lines represent residents from neighborhoods with a lower education level. The 2 graphs at the top of the Figure, the 2 graphs in the middle of the Figure, and the 2 graphs at the bottom of the Figure were determined with different samples including each time only 2 different quartiles of neighborhood education (the first and fourth quartiles on the top, the second and fourth quartiles in the middle, and the third and fourth quartiles at the bottom). The fourth quartile (high educated neighborhoods) was considered as the reference group in all 3 samples, to compute the probability of living in a neighborhood with a lower education level.

TABLE 4. Initial Sample Sizes and Their Percentage of Reduction After Propensity Score Matching for BMI and Waist Circumference (as Detailed in Figure 1, 3 Separate Samples Were Constructed Through Propensity Score Matching), Stratified by Sex, Paris Metropolitan Area, 2007–2008

	Men				Women			
	BMI Sample		Waist Circumference Sample		BMI Sample		Waist Circumference Sample	
Variable	Initial Sample Size No.	Reduction in Sample Size After Matching %	Initial Sample Size No.	Reduction in Sample Size After Matching %	Initial Sample Size No.	Reduction in Sample Size After Matching %	Initial Sample Size No.	Reduction in Sample Size After Matching %
Neighborhood education								
First and fourth quartiles	2368	56.7	2329	57.0	1246	58.6	1208	58.6
Second and fourth quartiles	2368	30.9	2330	30.9	1247	35.0	1208	36.3
Third and fourth quartiles	2368	16.8	2330	16.8	1247	17.2	1209	17.8

TABLE 5. Associations Between Neighborhood Education Level (500 m) and BMI or Waist Circumference Based on the Entire Sample and on the Propensity-score Matched Samples Stratified by Sex, Paris Metropolitan Area, 2007–2008

	Men				Women			
	BMI (kg/m^2)		Waist Circumference (cm)		BMI (kg/m^2)		Waist Circumference (cm)	
Education	β[a] (95% CI)	CI Width Change[b]	β[a] (95% CI)	CI Width Change[b]	β[a] (95% CI)	CI Width Change[b]	β[a] (95% CI)	CI Width Change[b]
Entire sample								
Fourth quartile (high)[c]	0.00		0.00		0.00		0.00	
Third quartile (medium-high)	0.18 (−0.12 to 0.48)		0.14 (−0.72 to 1.01)		0.12 (−0.39 to 0.63)		0.24 (−0.97 to 1.46)	
Second quartile (medium-low)	0.35 (0.04 to 0.65)		0.59 (−0.29 to 1.47)		0.42 (−0.11 to 0.95)		0.70 (−0.55 to 1.95)	
First quartile (low)	1.01 (0.68 to 1.34)		2.22 (1.26 to 3.18)		1.79 (1.21 to 2.38)		3.96 (2.57 to 5.35)	
Propensity score matched samples								
Fourth quartile (high)[c]	0.00		0.00		0.00		0.00	
Third quartile (medium-high)	0.06 (−0.25 to 0.36)	+1.67%	−0.14 (−1.05 to 0.76)	+4.62%	0.11 (−0.38 to 0.60)	−3.92%	0.02 (−1.21 to 1.26)	+1.65%
Second quartile (medium-low)	0.18 (−0.17 to 0.53)	+14.75%	0.38 (−0.63 to 1.39)	+14.77%	0.30 (−0.30 to 0.90)	+13.21%	0.59 (−0.91 to 2.08)	+19.6%
First quartile (low)	0.85 (0.40 to 1.30)	+36.36%	1.94 (0.63 to 3.25)	+36.46%	2.19 (1.25 to 3.14)	+61.54%	3.94 (1.71 to 6.17)	+60.43%

[a]The regression coefficients β are expressed in kg/m^2 in the model for BMI and in cm in the model for waist circumference.
[b]Percentage of change in CI width when comparing the entire sample with the propensity score matched samples.
[c]Reference category.

sample, consistent with the intermediate level of social segregation observed in France. Regarding 95% CIs, our propensity-score matching strategy is useful to diagnose situations in which measures of uncertainty are spuriously narrow in the analyses based on the entire sample. If an association is documented in the entire sample, but the 95% CI of the association becomes too large in the reduced propensity-score matched sample to document any association, we would conclude that the association documented in the initial sample had an excessively narrow CI (because it included too many unexchangeable participants who are not usable in the determination of the adjusted neighborhood effect). On the other hand, 95% CIs are perhaps excessively large in the propensity-score matching analyses (conservative analyses), in that an excessive number of participants are excluded from the sample (regression models require data in all cells of the cross-tabulation, not a strict balance in the number of participants between exposure groups at each level of the propensity score).

Overall, the estimations obtained from the propensity-score matched samples are not intended to replace those derived from the entire sample, but rather are meant to provide information allowing assessment of the quality of the associations obtained from the full sample. We do not necessarily view the estimates and related measures of uncertainty from propensity-score matched samples as better than those derived from the entire sample, or as a better trade-off between validity and precision. We recommend that future studies provide the estimates of neighborhood effects obtained for the entire sample (more generalizable), and comparatively those from propensity-score matched samples, to validate that the adjusted neighborhood effect can be estimated without excessive model extrapolations.

Although propensity-score matching is informative when estimating contextual effects, this method does not solve in itself issues of residual confounding related to the selective migration of participants toward specific neighborhoods.[16] The critical question is the selection of variables to include in the propensity-score calculation.[18,37] Although we attempted to ensure that persons are exchangeable on the basis of several characteristics, a major study limitation is that important individual variables related both to the choice of living in a particular type of neighborhood and to weight were not available in the database (eg, general attitudes toward own body weight and residential strategies), resulting in a misspecification of the propensity score.

In summary, studies that measure and model neighborhood socioeconomic effects should include sensitivity analyses of the buffer-area size to identify the spatial scale on which the environment–health associations operate. Propensity score matching can be implemented to verify that modeling results are not based on excessive extrapolations.

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