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How do environmental characteristics jointly contribute to cardiometabolic health? A quantile g-computation mixture analysis

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ABSTRACT

Accumulating evidence links cardiometabolic health with social and environmental neighborhood exposures, which may contribute to health inequities. We examined whether environmental characteristics were individually or jointly associated with insulin resistance, hypertension, obesity, type 2 diabetes, and metabolic syndrome in San Diego County, CA. As part of the Community of Mine Study, cardiometabolic outcomes of insulin resistance, hypertension, BMI, diabetes, and metabolic syndrome were collected in 570 participants. Seven census tract level characteristics of participants' residential environment were assessed and grouped as follows: economic, education, health care access, neighborhood conditions, social environment, transportation, and clean environment. Generalized estimating equation models were performed, to take into account the clustered nature of the data and to estimate β or relative risk (RR) and 95 % confidence intervals (CIs) between each of the seven environmental characteristics and cardiometabolic outcomes. Quantile g-computation was used to examine the association between the joint effect of a simultaneous increase in all environmental characteristics and cardiometabolic outcomes. Among 570 participants (mean age 58.8 ± 11 years), environmental economic, educational and health characteristics were individually associated with insulin resistance, diabetes, obesity, and metabolic syndrome. In the mixture analyses, a joint quartile increase in all environmental characteristics (i.e., improvement) was associated with decreasing insulin resistance (β, 95 %CI: −0.09, −0.18–0.01)), risk of diabetes (RR, 95 %CI: 0.59, 0.36–0.98) and obesity (RR, 95 %CI: 0.81, 0.64–1.02). Environmental characteristics synergistically contribute to cardiometabolic health and independent analysis of these determinants may not fully capture the potential health impact of social and environmental determinants of health.

1. Introduction

Social determinants of health, the conditions in which people are born, grow, live, work and age, contribute to explaining observed inequalities in a variety of health outcomes (Marmot, 2015). These conditions are driven by the distribution of power, money, and resources (Marmot and Bell, 2012) at both the individual and neighborhood levels. The social gradient in health is well documented, but its amplitude varies across geographical contexts. In the United States (US), health disparities remain large (Singh et al., 2017; Braveman et al., 2010; National Academies of Sciences, Engineering, and Medi-cine, 2017), especially for cardiometabolic diseases (Safford et al., 2021; Havranek et al., 2015). Environmental determinants (broadly defined), including environmental hazards, public infrastructures, built environment, as well as economic, social, health, and educational characteristics, may have a major role on these health disparities. Accumulating epidemiological evidence demonstrates that these environmental determinants are important factors of cardiometabolic disease risk (Havranek et al., 2015; Bhatnagar, 2017).

Cardiovascular disease (CVD) is a leading economic and medical burden in the US. CVD is the most frequent cause of death in the US, and approximately 655,000 Americans die prematurely from heart disease

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each year (Virani et al., 2020). By 2030, 40 % of the US population is projected to have one or more forms of CVD (Heidenreich et al., 2011). It is estimated that CVD is 50–90 % modifiable and preventable (Bhatnagar, 2017). Cardiometabolic outcomes, such as cholesterol, blood pressure level, or insulin resistance represent a critical point of intervention to reduce CVD burden. In this context, environmental determinants may constitute a promising avenue for CVD prevention.

Neighborhood deprivation (mainly assessed using principal components analysis based on census tract-level socioeconomic variables such as income, education or employment) has been associated with higher CVD mortality and contributes to CVD risk independently of individual-level socioeconomic measures (Diez Roux, 2003; Akwo et al., 2018; Xiao et al., 2018). Residing in a deprived neighborhood is also associated with increased prevalence of obesity (Powell-Wiley et al., 2013), weight gain (Powell-Wiley et al., 2014), accelerated longitudinal blood pressure elevation and incident hypertension (Claudel et al., 2018), impaired glycemic control and type 2 diabetes (Alvarez-Ramos et al., 2020), insulin resistance (Heald et al., 2017), and metabolic syndrome (MetS) (Keita et al., 2014). Improving the environment quality could lead to improved population cardiometabolic health throughout the life course and ultimately reduce environmental health inequities.

Environmental determinants of cardiometabolic health are complex and include many dimensions: natural, social, and material that do not act independently from each other. However, previous studies typically analyzed the role of such environmental determinants individually or by using composite indexes (Woodward et al., 2007; Bevan et al., 2021), potentially leading to methodological and statistical issues. First, environmental determinants are often highly correlated, driven by similar structural factors, which can lead to multi collinearity posing a challenge for inferential studies. Second, while composite indexes allow for the combination of multiple exposures into a single standardized index, their interpretation becomes ambiguous. The single value may be driven by different contributing factors and may hinder practical recommendations when designing interventions. Mixture methods such as the quantile g-computation approach have been developed to assess several exposures simultaneously, and are designed to estimate both independent and joint effects of exposures (Keil et al., 2020). Such approaches can shed light on how environmental conditions jointly impact cardiometabolic health.

In this study, we examined the association between seven distinct environmental characteristics (economic, education, healthcare access, neighborhood conditions, transportation, social environment, and clean environment) and five measures of cardiometabolic health (insulin resistance, hypertension, obesity, type 2 diabetes, and metabolic syndrome). Data used was from the Community of Mine Study, a cross-sectional study in an ethnically diverse population in San Diego, CA. We assessed the impact of the seven environmental characteristics individually with generalized estimating equation models, and jointly using quantile g-computation.

2. Methods

2.1. Study population

The Community of Mine Study was an observational study conducted from 2014 to 2017 in San Diego County, CA. The protocol and inclusion criteria have been described previously (Jankowska et al., 2019). This study includes 602 adults aged 35–80 years old living for at least 6 months in study census block group, which were selected to maximize environmental variation. The main objective of the Community of Mine Study is to advance methods of cancer risk exposure assessment by measuring participant access and exposure to various environments. Participants attended a clinical visit where blood pressure, height, weight, and hip/waist circumference were recorded, and blood and urine samples were collected. Demographic characteristics (e.g., age, gender, race/ethnicity) were collected via self-report survey. For this study, we conducted a completed analysis. Study ethics approval was obtained from the UCSD IRB (protocol #140510). Signed informed consent was obtained from all participants.

2.2. Exposure assessment

This study focused on seven environmental characteristics (details in Supplementary Table 1), that have been shown in previous research to be directly or indirectly associated with cardiometabolic risk factors: (1) economic, (2) education, (3) health care access, (4) neighborhood conditions, (5) social environment, (6) transportation, and (7) clean environment. These characteristics were based on indicators available from online public sources: U. S. Census Bureau's American Community Survey (ACS), California Environmental Protection Agency (CalEPA), Alcoholic Beverage Commission (ABC), Green Info (parks), the National Land Cover Database (tree canopy), US Department of Food and Agriculture (supermarket access), US Environmental Protection Agency (retail density), and University of California, Berkeley (voter participation).

We adopted these indicators following the work by the Public Health Alliance of Southern California who developed the California Healthy Place Index (Public Health Alliance of Southern California, 2018). For each census tract, each indicator was transformed into a standardized scale (z-score) of increasing advantage and averaged for each characteristic (economic, education, health care access, neighborhood conditions, social environment, transportation, and clean environment). These indicators used data from the 2011 to 2015 time period (the exact date of measurement for each indicator was detailed in Table S1). Economic characteristics included poverty, employment, and income indicators. Education characteristics was based on the percentage of preschool enrollment, high-school enrollment, and bachelor attainment. Health care access was based on percentage of insured adults. Neighborhood characteristics included retail jobs, supermarket access, parks, tree canopy, and presence of alcohol establishments. Social characteristics included two parent household and voting indicators. Transportation characteristics included a healthy commuting indicator (percentage of workers commuting by walking, cycling, or transit) and automobile access. Clean environment characteristics included concentrations of diesel PM, Ozone, $PM_{2.5}$, and drinking water contaminant index. For the seven global characteristics, higher values indicated greater advantage. These environmental characteristics were assigned to participant's census tract based on their home address.

2.3. Cardiometabolic outcomes

We focused on five cardiometabolic outcomes assessed from 2014 to 2017: obesity, hypertension, type 2 diabetes, insulin resistance, and metabolic syndrome. Obesity was defined by a body mass index (BMI) greater than or equal to 30 kg/m^2. Hypertension was dichotomized in two categories according to blood pressure level: normal or pre-hypertension ($\leq$129 mmHg systolic and $<$80 mmHg diastolic) vs hypertension ($\geq$130 mmHg systolic or $\geq$80 mmHg diastolic). Type 2 diabetes was defined by a blood glucose level higher than 125 mg/dL. Insulin resistance was assessed using the Homeostatic Model Assessment of Insulin Resistance (HOMA-IR) (Matthews et al., 1985). The HOMA-IR index was calculated according to the formula: fasting plasma insulin (mlU/L) $\times$ fasting plasma glucose (mg/dL) /22.5. Using the NCEP ATP III definition (Huang, 2009), the presence of Metabolic Syndrome (MetS) (yes/no) was indicated based the presence of at least three of the following: 1) increased waist circumference ($>$102 cm [$>$40 in] for men, $>$88 cm [$>$35 in] for women); 2) elevated triglycerides ($\geq$150 mg/dL); 3) low HDL cholesterol ($<$40 mg/dL in men, $<$50 mg/dL in women); 4) hypertension ($\geq$130/$\geq$80 mmHg); and 5) impaired fasting glucose ($\geq$110 mg/dL).

2.4. Statistical analysis

2.4.1. Single environmental characteristics analysis

First, we performed generalized estimating equations (GEE) models with exchangeable matrixes accounting for participants clustering within census tracts. We used modified Poisson regressions to account for the high prevalence of the binary outcomes of interest (Knol et al., 2012). For insulin resistance (HOMA-IR index), we used a linear model. All models were adjusted for age, sex, ethnicity (Hispanic/Latino vs non-Hispanic), income (coded into 3 categories: less then 30 k, 30 k−55 k, >55 k), and current smoking status (yes, no). BMI (categorized into lean/normal (<24.9 kg/m^2), overweight (25–29.99 kg/m^2), and obese (≥30 kg/m^2)) was further included as a supplementary covariate for insulin resistance, type 2 diabetes, and hypertension outcomes. Environmental characteristics were considered as continuous variables (transformed by dividing by IQR/2), and then categorized into quartiles to look at potential non-linear relationships.

2.4.2. Mixture approach

We first examined Spearman correlations between each of the environment determinants. Then, for analyzing the effects of exposure mixture, we used quantile g-computation. Quantile-g-computation is a parametric, generalized-linear-model–based approach that uses a basic implementation of g-computation to estimate a mixture effect (Keil et al., 2020; Robins, 1986). In this study, quantile g-computation estimates the parameters of a marginal structural model that characterizes the change in the expected cardiometabolic outcomes (insulin resistance, hypertension, obesity, type 2 diabetes, metabolic syndrome) given a joint intervention on all exposures, conditional on confounders (sex, age, race/ethnicity, income, smoking and BMI - except for obesity and MetS models). Quantile g-computation yields estimates of the effect of increasing all exposures by one quantile, simultaneously. Thus, it estimates a “mixture effect”. We employed quantile g-computation with Poisson regression for all outcomes except HOMA-IR index for which we used a linear regression. The estimated coefficient ψ is interpretable as the RR of changing (by increasing) all exposures by one quartile at the same time. This approach also provides weights that indicate the contribution of the individual components of the mixture to the overall estimate. Finally, we examined effect measure modification by gender, race/ethnicity, age, and income, and compared effect estimates from stratified analyses by using a Cochran *Q* test for heterogeneity. We used the same quantile values across categories of each stratifying variable. The R package qgcomp was used to implement g-computation for analyzing the effects of exposure mixtures (https://cran.r-project.org/web/packages/qgcomp/vignettes/qgcomp-vignette.html). All analyses were performed with RStudio Version 3.6.5.

3. Results

3.1. Study population

Among the 602 participants from the Community of Mine Study, we restricted our analyses to the participants with complete data for exposures, covariates, and outcomes (Figure S1). Finally, 570 participants (and 566 participants for diabetes and HOMA-IR measures) were included in the analytical sample. Among the 570 participants, 318 were female (55.8 %) and 241 were Hispanic/Latino (42.3 %) (Table 1). The mean (SD) age was 58.8 years (11.0). Among them, 198 (34.7 %) were obese, 49 (8.7 %) had type 2 diabetes, 133 (23.3 %) had hypertension and 114 (20 %) had metabolic syndrome. The median (IQR) of HOMA-IR was 2.1 (1.3–3.6).

3.2. Single environmental characteristics analysis

The spatial distribution of the exposures in the study geographical area is presented in Figure S2, which shows important variability across census tracts in San Diego County suggesting that risk factors are unevenly distributed and could influence the cardiometabolic outcomes incidence distribution.

Table 1
Distribution of participants characteristics from the Community of Mine Study (N = 570).

n, (%)	
Socioeconomic characteristics	
Female	318 (55.8)
Age[a]	58.8 (11.0)
Hispanics/Latinos	241 (42.3)
Income	
<30 k	161 (28.2)
30 k to 55 k	134 (23.5)
>55 k	275 (48.2)
Cardiometabolic outcomes	
HOMA-IR[b] (N = 566)	2.1 (1.3–3.6)
Obesity	198 (34.7)
Diabetes (N = 566)	49 (8.7)
Hypertension	133 (23.3)
Presence of MetS (N = 565)	114 (20.0)

HOMA-IR: Homeostatic Model Assessment of Insulin Resistance; MetS: Metabolic Syndrome.
Obesity: BMI ≥ 30 kg/m2. Hypertension: ≥130 mmHg systolic or ≥ 80 mmHg diastolic. Type 2 diabetes: blood glucose level > 125 mg/dL. Insulin resistance using the HOMA-IR: fasting plasma insulin (mlU/L) × fasting plasma glucose (mg/dL) /22.5. MetS: presence of at least three of the following: waist circumference > 102 cm for men, >88 cm for women; triglycerides ≥ 150 mg/dL; HDL cholesterol < 40 mg/dL in men, <50 mg/dL in women; hypertension ≥ 130/≥80 mmHg; and fasting glucose ≥ 110 mg/dL.
[a] mean (SD).
[b] median (IQR).

When analyzing exposures individually (Table 2), insulin resistance level was lower when environmental economic, educational and health characteristics were higher (indicating greater advantage) (adjusted β (95 % CI): −0.05 (-0.10–0.01), −0.04 (-0.08–0.01), −0.04 (-0.08–0.01), respectively). When an individual lived in an area with high rates of economic and educational attainment and high rates of health insurance, the risk of obesity was reduced (adjusted RR (95 % CI): 0.86 (0.77–0.95), 0.90 (0.83–0.98), 0.92 (0.85–0.99), respectively). The risk of diabetes was also reduced when participants lived in environments with better economic and healthcare indicators (adjusted RR (95 % CI): 0.68 (0.52–0.89), 0.72 (0.60–0.86), respectively). Moreover, a negative association was identified between environmental educational characteristic and metabolic syndrome (adjusted RR (95 % CI): 0.85 (0.76–0.96)). For the neighborhood, social and clean environment characteristics, we did not identify any association. We were not able to detect any association between hypertension and any of the exposures. These associations were consistent when exposures were categorized in quartiles (Table S2).

3.3. Mixture analysis

Most environmental characteristics were correlated. Figure S3 illustrates Spearman correlations among the seven environmental characteristics scores. Economic, educational, social, and healthcare characteristics tended to have high correlations with each other (ρ ≥ 0.60). This high correlation structure lends to the use of a mixture analysis (i.e., quantile g-computation).

In the quantile g-computation model (Table 3), changing all environmental characteristics by one quartile at the same time (i.e., improving the overall characteristics of the environment) while considering the collinear structure, was negatively associated with insulin resistance (β (95 % CI): −0.09 (−0.18–0.01)). The quantile g-computation RR estimates (95 % CI) were 0.93 (0.69–1.24) for hypertension, 0.81 (0.64–1.02) for obesity, 0.59 (0.36–0.98) for diabetes and

Table 2
Associations between continuously measured environmental characteristics and cardiometabolic outcomes (N = 570).

	Economic	Education	Health care access	Neighborhood	Social	Transportation	Clean environment
β (95 % CI)							
Insulin Resistance (N = 566)	−0.05 (−0.10–0.01)	−0.04 (−0.08–0.01)	−0.04 (−0.08–0.01)	0.00 (−0.03–0.02)	−0.01 (−0.06–0.04)	−0.02 (−0.04–0.01)	0.01 (−0.02–0.03)
RR (95 % CI)							
Hypertension	0.92 (0.81–1.05)	1.01 (0.90–1.13)	0.94 (0.84–1.05)	0.99 (0.91–1.07)	0.96 (0.85–1.08)	0.98 (0.92–1.04)	1.01 (0.94–1.08)
Obesity	0.86 (0.77–0.95)	0.90 (0.83–0.98)	0.92 (0.85–0.99)	0.96 (0.91–1.02)	0.92 (0.83–1.01)	0.97 (0.92–1.02)	1.03 (0.98–1.08)
Diabetes (N = 566)	0.68 (0.52–0.89)	0.90 (0.74–1.08)	0.72 (0.60–0.86)	0.95 (0.85–1.06)	0.88 (0.69–1.11)	0.89 (0.78–1.01)	0.98 (0.88–1.10)
MetS (N = 565)	0.97 (0.82–1.14)	0.85 (0.76–0.96)	0.97 (0.85–1.10)	0.93 (0.87–1.00)	1.14 (0.98–1.33)	0.96 (0.89–1.04)	1.04 (0.97–1.13)

HOMA-IR: Homeostatic Model Assessment of Insulin Resistance; MetS: Metabolic Syndrome.
Obesity: BMI ≥ 30 kg/m2. Hypertension: ≥130 mmHg systolic or ≥ 80 mmHg diastolic. Type 2 diabetes: blood glucose level > 125 mg/dL. Insulin resistance using the HOMA-IR: fasting plasma insulin (mlU/L) × fasting plasma glucose (mg/dL) /22.5. MetS: presence of at least three of the following: waist circumference > 102 cm for men, >88 cm for women; triglycerides ≥ 150 mg/dL; HDL cholesterol < 40 mg/dL in men, <50 mg/dL in women; hypertension ≥ 130/≥80 mmHg; and fasting glucose ≥ 110 mg/dL.
Models were adjusted for sex, age, race/ethnicity, income, smoking and BMI (except for obesity and MetS).

Table 3
Quantile g-computation estimates for the association between increasing all the environmental characteristics by a quartile within the overall mixture (N = 570).

Cardiometabolic outcomes	Quantile g-computation estimates*
	β (95 % CI)
Insulin Resistance (N = 566)	−0.09 (−0.18–0.01)
	RR (95 % CI)
Hypertension	0.93 (0.69–1.24)
Obesity	0.81 (0.64–1.02)
Diabetes (N = 566)	0.59 (0.36–0.98)
MetS (N = 565)	0.87 (0.64–1.19)

HOMA-IR: Homeostatic Model Assessment of Insulin Resistance; MetS: Metabolic Syndrome.
Obesity: BMI ≥ 30 kg/m2. Hypertension: ≥130 mmHg systolic or ≥ 80 mmHg diastolic. Type 2 diabetes: blood glucose level > 125 mg/dL. Insulin resistance using the HOMA-IR: fasting plasma insulin (mlU/L) × fasting plasma glucose (mg/dL) /22.5. MetS: presence of at least three of the following: waist circumference > 102 cm for men, >88 cm for women; triglycerides ≥ 150 mg/dL; HDL cholesterol < 40 mg/dL in men, <50 mg/dL in women; hypertension ≥ 130/≥80 mmHg; and fasting glucose ≥ 110 mg/dL.
*Models were adjusted for sex, age, race/ethnicity, income, smoking and BMI (except for obesity and MetS).

0.87 (0.64–1.19) for metabolic syndrome.

The weights representing the proportion of the positive or negative partial effect in the quantile g-computation models were shown in Fig. 1. For obesity, the environmental characteristics with the highest negative weights (i.e., those who contribute the most to the association) included economic, education, and health care access. For diabetes, the environmental characteristic with the highest negative weights was health care access, and for insulin resistance, it was educational characteristics.

When we stratified by gender, ethnicity, age, or income (Table S3), associations for the mixture analysis were more pronounced (especially for insulin resistance, obesity, and diabetes) among women in comparison to men, among non-Hispanic in comparison to Hispanic/Latino participants, and among older (age ≥ 60) than among younger participants. We identified heterogeneous effect for the association between environmental characteristics and obesity according to ethnicity. The positive effect of improving all environmental characteristics by one quartile on obesity was found only among non-Hispanics participants (Cochran test p-value: 0.04).

4. Discussion

Among the Community of Mine Study in San Diego County, we examined the effect of seven environmental characteristics individually and as a mixture on cardiometabolic health. We found that living in area where the environmental educational, economic, and health care access characteristics were good was associated with reduced insulin resistance (i.e., HOMA-IR level), and lower risk of type 2 diabetes, obesity, and metabolic syndrome. We also considered the important collinearity between these exposures and employed a mixture analysis to investigate the potential effect of environmental changes simultaneously. Using g-computation analysis, we estimated that a simultaneous increase (i.e., improvement) in all environmental characteristics by a quartile was associated with a reduced level of HOMA-IR and a decreased risk of type 2 diabetes and obesity. These joint effects were mostly driven by health care access, economic, and educational characteristics.

Previous studies have highlighted an effect of living environment on cardiometabolic health, especially with neighborhood deprivation (Claudel et al., 2018; Alvarez-Ramos et al., 2020; Heald et al., 2017; Keita et al., 2014) or air pollution (Yu et al., 2020; Kim et al., 2019). Generally, these studies look at single exposures, adjusting for some other environmental exposures or using a composite score. Quantile g-computation has recently been proposed to study the effects of complex exposure mixtures. This approach has been used to assess exposures such as metal (White et al., 2020; Xu et al., 2020; Niehoff et al., 2020) and chemicals (Lebeaux et al., 2020; Lin et al., 2021; Parada et al., 2021). To the best of our knowledge, only one study used g-computation to examine the effect of social/environmental exposure mixtures on fetal growth (Goin et al., 2020).

To identify effective interventions and translate from the evidence to reductions in CVD, we need to obtain unbiased effect estimates linking environmental determinants and cardiometabolic health. Causal inference regarding the effects of environmental determinants of health is challenging because adverse exposures tend to spatially cluster, so it is difficult to isolate the effect of, for example, living in a low-income area from living in a polluted area. Quantile g-computation, an approach initially developed to study chemical mixtures, evaluates the joint effects of multiple environmental characteristics, rather than single characteristics, and allows accurate identification of risk factors and assessment of interactions (Bellavia et al., 2019). This approach allows for development of more realistic and targeted public health interventions. Realistic because we know that environmental characteristics are correlated, thus changing geographical distributions of money and resources will impact several environmental characteristics, from access to health care to air pollution. Targeted because we can distinguish which specific modifiable environmental characteristics will impact cardiometabolic health the most.

Environmental cardiovascular health inequities can be explained by differences in medical access, material deprivation, behavioral differences (diet, physical activity), exposure to psychosocial stressors, exposure to physical characteristics like built environment (buildings, natural areas, parks, transport infrastructures), or exposure to physical

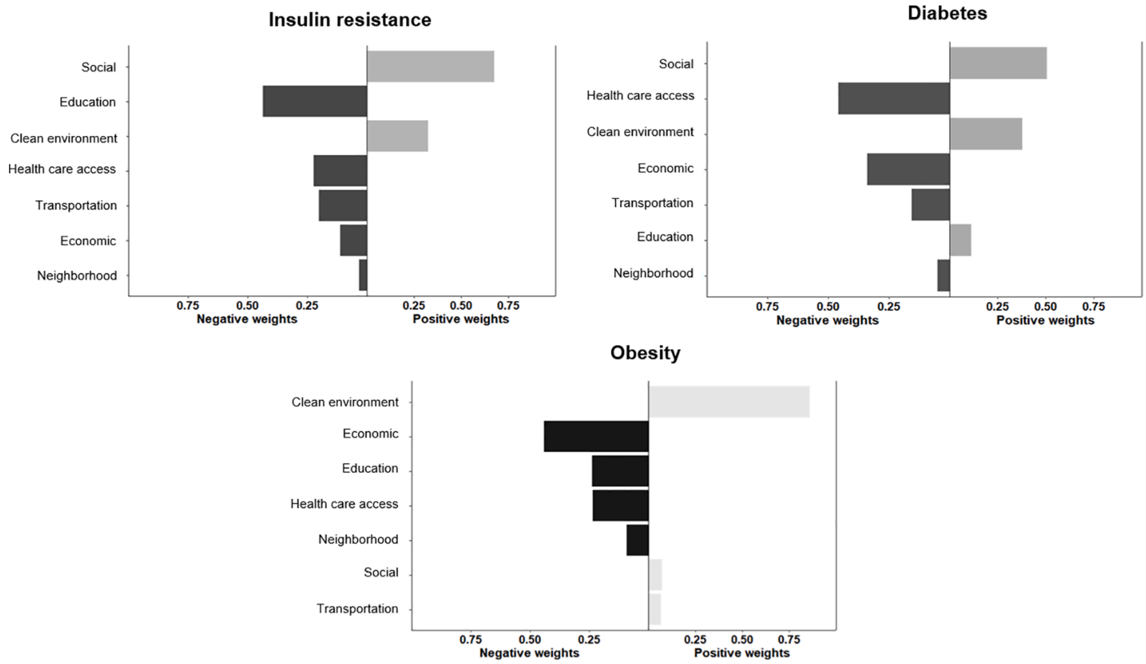

Fig. 1. Weights representing the proportion of the positive or negative partial effect in the quantile g-computation models.

environmental hazards (air pollution, noise) (Bhatnagar, 2017). Using quantile g-computation, we can see which characteristic contributes the most to the association. In this study, the largest positive effects on cardiometabolic health were mainly due to compositional variables (e.g., percentage of population employed, enrolled in school, or insured in the census tract) and, to a lesser extent, to contextual variables like neighborhood and clean environment. This finding confirms the importance of neighborhood determinants on cardiometabolic outcomes and highlights the synergistic effects of such contextual and compositional determinants. This helps solving the dualism of "context" and "composition" related to their tightly interrelation, and the mutually reinforcing and reciprocal relationship between people and place, as explain by Cummins et al. (Cummins et al., 2007).

The strengths of our study include biomarker measurement and inclusion of large numbers of Hispanic participants. For the first time, we employed recently developed analytic methods by Keil et al, the quantile g-computation to assess the association between environmental determinants and cardiometabolic outcomes. This approach is an extension of WQS regression with several advantages due to the flexibility of g-computation, for example quantile g-computation does not require a directional homogeneity assumption (Keil et al., 2020). However, it will be interesting to explore the deviations of linearities in relation to the mixture in future studies.

5. Limitations

Our study has also several limitations. First, our population sample is small, and participants were recruited in San Diego County limiting the generalization of these results. Second, environmental characteristics were assessed at the census tract level, which are imperfect proxies for the places in which people live their lives (Osypuk et al., 2007). Third, this is a cross sectional study and so environmental characteristics, and health measures were assessed at one time point. We know that exposure timing and duration could be important to consider, as they may have different effects on individuals throughout the life course due to physiologically sensitive developmental periods or socially defined periods of vulnerability (Glymour et al., 2014). Finally, even though our study includes an ethnically diverse population, it should be confirmed in other cohorts with more racial diversity.

6. Conclusions

Better understanding of how our multidimensional living environment alters cardiometabolic health informs us on how to effectively address environment-associated CVD using appropriate prevention policies. Our findings highlight the importance of jointly analyzing impacts of contextual and compositional neighborhood determinants of cardiometabolic health, to ultimately help reducing the global CVD burden and health inequalities.

CRediT authorship contribution statement

Noémie Letellier: Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Steven Zamora:** Data curation, Writing – review & editing. **Jiue-An Yang:** Data curation, Writing – review & editing. **Dorothy D. Sears:** Conceptualization, Writing – review & editing. **Marta M. Jankowska:** Conceptualization, Writing – review & editing. **Tarik Benmarhnia:** Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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