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Changes in air pollution exposure after residential relocation and body mass index in children and adolescents: A natural experiment study☆

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ABSTRACT

Air pollution exposure may affect child weight gain, but observational studies provide inconsistent evidence. Residential relocation can be leveraged as a natural experiment by studying changes in health outcomes after a sudden change in exposure within an individual. We aimed to evaluate whether changes in air pollution exposure due to residential relocation are associated with changes in body mass index (BMI) in children and adolescents in a natural experiment study. This population-based study included children and adolescents, between 2 and 17 years, who moved during 2011–2018 and were registered in the primary healthcare in Catalonia, Spain (N = 46,644). Outdoor air pollutants (nitrogen dioxides (NO_2), particulate matter <10 μm (PM_{10}) and <2.5 μm ($PM_{2.5}$)) were estimated at residential census tract level before and after relocation; tertile cut-offs were used to define changes in exposure. Routinely measured weight and height were used to calculate age-sex-specific BMI z-scores. A minimum of 180 days after moving was considered to observe zBMI changes according to changes in exposure using linear fixed effects regression. The majority of participants (60–67% depending on the pollutant) moved to areas with similar levels of air pollution, 15–49% to less polluted, and 14–31% to more polluted areas. Moving to areas with more air pollution was associated with zBMI increases for all air pollutants (β NO_2 = 0.10 (95%CI 0.09; 0.12), β $PM_{2.5}$ 0.06(0.04; 0.07), β PM_{10} 0.08(0.06; 0.10)). Moving to similar air pollution areas was associated with decreases in zBMI for all pollutants. No associations were found for those moving to less polluted areas. Associations with moving to more polluted areas were stronger in preschool- and primary school-ages. Associations did not differ by area deprivation strata. This large, natural experiment study suggests that increases in outdoor air pollution may be associated with child weight gain, supporting ongoing efforts to lower air pollution levels.

1. Introduction

Overweight and obesity in childhood and adolescence have serious social, economic and health implications in society, with various short- and long-term adverse health outcomes (Geserick et al., 2018; Kumar & Kelly, 2017). This chronic, multifactorial condition is a consequence of an interaction of genes, lifestyle behaviors, physiological and social determinants, and potentially environmental exposures, such as air pollution (González-Muniesa et al., 2017). Air pollution is one of the most harmful environmental and occupational risk factors, which contributed, according to the 2019 Global Burden of Disease study, to

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Abbreviations

BMI	Body mass index
NO_2	Nitrogen dioxides
PM_{10}	Particulate matter <10 μm
$PM_{2.5}$	Particulate matter <2.5 μm
SES	Socioeconomic status
SIDIAP	Information System for Research in Primary Care
zBMI	Body mass index z-scores

6.67 million deaths worldwide (Murray et al., 2020).

A growing body of evidence has linked exposure to outdoor, traffic-related, air pollution to increases in body mass index (BMI), overweight and obesity in childhood, but evidence is inconsistent and important questions remain about the causality of this association (An et al., 2018a,b; Malacarne et al., 2022; Wang et al., 2021). Several longitudinal and cross-sectional studies have reported that greater levels of air pollution are associated with higher weight among children and adolescents (Bloemsma et al., 2019; de Bont et al., 2019, 2021; Dong et al., 2015; Huang et al., 2019; Jerrett et al., 2014; Zhang et al., 2021), but others have reported null associations (Alderete et al., 2017; Fioravanti et al., 2018; Frondelius et al., 2018). Observational studies may be prone to residential self-selection, where more health-conscious individuals may choose to live in healthier areas (de Bont et al., 2019; Dong et al., 2015), and they may be prone to residential confounding by socioeconomic status (Malacarne et al., 2022). For these reasons, they may have limited capability to establish causality.

Natural experiments may offer a way to overcome some of the concerns of observational studies. Of particular relevance to outdoor air pollution, residential relocation studies offer the opportunity to study changes in health outcomes after a sudden change in air pollution levels due to the move to a different address. The value of natural experiments in providing real-world conditions has increased interest in the area of obesity prevention in the past two decades, however the body of research remains small (Crane et al., 2020). Even though subjects may self-select whether and to which type of neighborhood they move based on multiple unmeasured social and economic factors (Drewnowski et al., 2019), residential relocation experiments allow the consideration of changes in exposures and outcomes within individuals over a certain period (Braun et al., 2016). This improves the issue of residential self-selection and controls for time-invariant confounding. In this way, relocation studies have the potential to improve causal evidence. Residential relocation designs have been used in a small number of studies to evaluate the impact of changes in air pollution and traffic exposure on overall and specific causes of mortality, and myocardial infarction (Chen et al., 2021; Gan et al., 2010; Hart et al., 2013), but they have not been used to improve causal evidence for the association between air pollution and childhood obesity related outcomes.

In this context, the present study aimed to evaluate the association between changes in exposure to air pollution due to residential relocation and BMI z-scores (zBMI) in children and adolescents in a large population-based cohort using a natural experiment study design.

2. Methods

2.1. Study design, setting and population

This study used longitudinal retrospective data from the Information System for Research in Primary Care (SIDIAP) in Catalonia, Spain (Bolíbar et al., 2012). SIDIAP is an electronic health record dataset that contains pseudo-anonymized information of more than 6 million people from over 328 primary care centers, which represents around 75% of the population living in Catalonia. The SIDIAP dataset is highly representative of the entire Catalan region, according to sex, age and geographic distribution (Recalde et al., 2022).

Overall, 46,644 children and adolescents aged 2–17 years, who moved once between January 2011 and December 2018, with at least one anthropometric measurement (i.e., weight and height) recorded at the same visit and with at least one air pollution and zBMI measurement before and after moving were included in the study (Fig. 1). Since changes of addresses were only registered at an annual basis in SIDIAP, the date of moving was considered to be the midpoint of the moving year, i.e., June 30th (Chen et al., 2021). The estimation of moving in the middle of the year corroborates with the seasonality of mobility, in which a higher proportion of individuals move during summer time in Europe, between June and September (Tucker et al., 1995). Childhood obesity community-based interventions have shown short-term post-intervention effects on weight (Magarey et al., 2011; Smith et al., 2013), so a minimum time period of 180 days was considered to observe potential effects on zBMI. The choice for this time period took into account the lack of residential relocation studies and effects of air pollution exposure on childhood zBMI and that the majority of relocation studies with lower risk of bias consider at least 180 days after moving, as described in a recent literature review on residential relocation studies and effects on various weight outcomes (Edwards et al., 2022). Current analyses were focused on one-time movers since the majority of movers only moved once during the study period and in order to ease interpretability of results.

Ethical approval was received by the Clinical Research Ethics Committee of the IDIAPJGol (project code: 22/019-P).

2.2. Anthropometric assessment

Weight (nearest of 100 g) and height (nearest 0.1 cm) were routinely measured following standard procedures in primary care centers (Generalitat de Catalunya, 2008). Age- and sex-specific zBMI were calculated and categories were described according to the World Health Organization (WHO) (de Onis, 2007; World Health Organization (WHO) Multicentre Growth Reference Study World Health Organization Multicentre Growth Reference Study Group, 2006): <5 years: Underweight < -2 standard deviations (SD), normal weight [− 2SD, 2SD], overweight]2SD, 3SD] and obesity > 3SD; ≥5 and ≤ 17 years: Underweight <−2SD, normal weight [− 2SD, 1SD], overweight]1SD, 2SD] and obesity >2SD. Biologically implausible values of weight, height and zBMI were removed and continuous zBMI was considered as the main outcome of this study.

2.3. Ambient air pollution assessment

Since SIDIAP is a pseudo-anonymized database, it does not contain individual personal data (such as name and address) of individuals. Therefore, exposure to outdoor air pollution was estimated at residential census tract level. Annual residential levels of nitrogen dioxides (NO_2), particulate matter (PM) < 10 μm (PM_{10}) and <2.5 μm ($PM_{2.5}$) were estimated using a land use regression model (LUR) developed within the ESCAPE framework for the whole of Catalonia (Beelen et al., 2013; Eeftens et al., 2012). LUR models have been increasingly used in epidemiological studies and enable the capture of within-city variability. $PM_{2.5}$, PM_{10} and NO_2 were the air pollutants of focus in this study, based on the WHO air quality guidelines from 2005 (World Health Organization (WHO). Regional Office for Europe, 2006) and 2021 (World Health Organization (WHO), 2021) which have shown dramatical increases worldwide and a high percentage of population living in areas that exceeded the WHO air quality guidelines for these pollutants. The Catalonian LUR model predicted (R^2) 62–76% of the variability in air pollution levels in 2009. To estimate exposure at census tract level, we created an artificial grid points data set with n random points within each census tract based on its area so increasing the density of points in smaller areas and reducing the number of points in

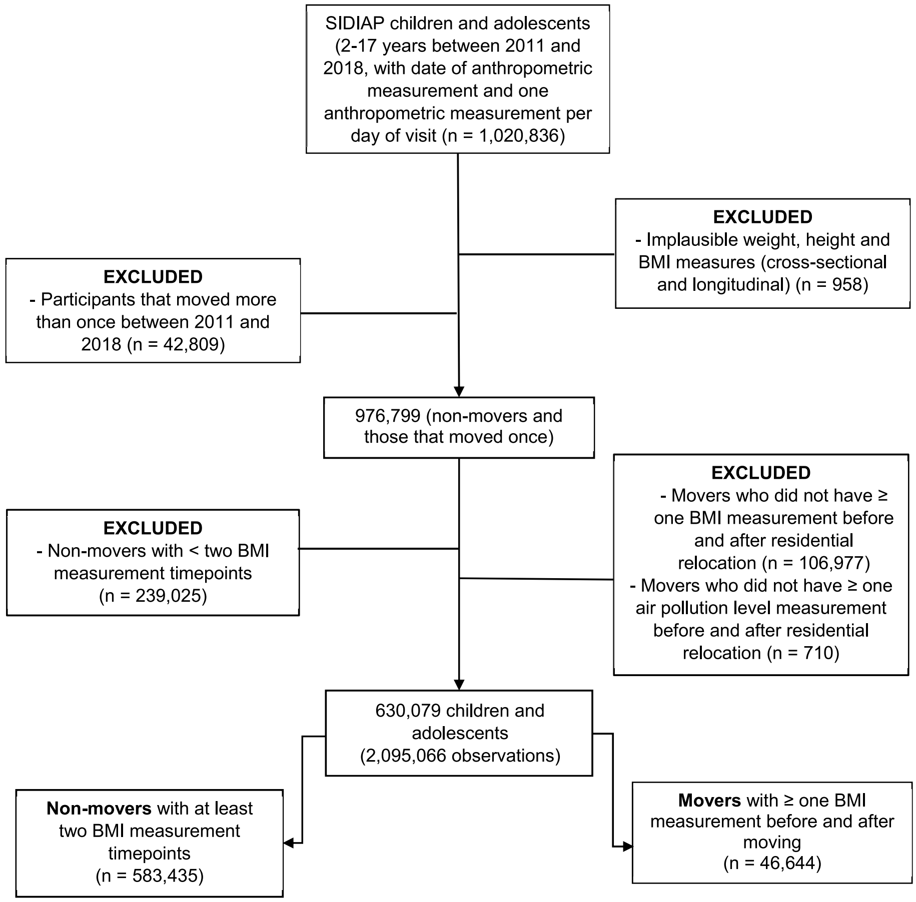

Fig. 1. Study flowchart.

larger areas. We ensured at least 5 observations predicted within each census area. Air pollution was then averaged by census area (Nieuwenhuijsen et al., 2018). Each study participant was assigned the level of air pollution at the residential census tract location before and after residential move. The measurement of air pollution concentrations at fixed location monitoring sites has been the most common and traditional approach used to assess air quality in cities, measure trends and estimate exposures in epidemiological studies.

Average annual concentrations of $PM_{2.5}$, PM_{10} and NO_2 were grouped in tertiles before residential relocation, since we were interested in substantial changes in air pollution levels, rather than small decreases/increases in air pollution levels. Tertile cut-offs were used to define changes in exposure before and after relocation, and the following categories of change were defined: “Moving to a less polluted area” included individuals for whom the air pollution tertile decreased after residential relocation, “Moving to a similar area” included individuals for whom the air pollution tertile did not change, and “Moving to a more polluted area” included individuals for whom the air pollution tertile increased after residential relocation.

2.4. Covariates: socioeconomic and built environment characteristics

Child and adolescent age were obtained through SIDIAP, besides sex and nationality (for descriptive purposes). As an indicator of area-SES, the *Índice de privación 2011 de la Sociedad Española de Epidemiología* (IP2011 deprivation index) (Duque et al., 2021), which is linked to each residential census area of the population in Spain (urban and rural areas), was used. The IP2011 deprivation index is based on six socioeconomic indicators, calculated for each census tract in 2011: Percentage of unemployment, manual and temporary workers, percentage of insufficient education (i.e., unable to read or write/incomplete primary studies) overall and among the younger population, and percentage of houses without internet access. Based on the distribution of our study population, the IP2011 deprivation index was categorized in quintiles, in which the 1st and the 5th quintile were the least and the most deprived areas, respectively. Finally, population density was calculated as the number of inhabitants divided by the census area (km^2), obtained through the Spanish National Statistics Institute of 2011.

2.5. Statistical analyses

We explored the association between the $PM_{2.5}$, PM_{10} and NO_2 exposure change categories and changes in child and adolescent zBMI using linear fixed effects regression models for panel data. Fixed effects models rely on within-person variation (Allison, 2005), allowing each individual to serve as his/her own control (Knuiman et al., 2014), besides controlling for observed and unobserved time-invariant individual characteristics (Lovasi & Goldsmith, 2014), such as underlying preferences and behaviors. The choice for fixed effects models was based on the assumption that the change in exposure is under the control of the individual, and not that changes in exposure are a function of decisions made outside of the unit of observation (e.g., a state policy change), as is the case of difference-in-difference analysis (Strumpf et al., 2017). Fixed effects models take advantage of the panel data structure (repeated data in the same people over time), whereas the differences-in-differences approach is more often used in population level (different people can be included in the pre- and post-intervention groups) (Griffin et al., 2021). The adjusted fixed effects models included mean-centered age, population density, the IP2011 deprivation index and an interaction term between mean-centered age and air pollution change. This interaction term was investigated based on the assumption that the effect of the exposure to air pollution on weight may differ/be dependent on child age.

Sensitivity analyses were performed to explore robustness of results: i) Stratification by age-groups (at baseline age) (preschool-age (2–5 years), primary school-age (6–11 years) and adolescence (12–17 years)); (ii) Inclusion of zBMI measurements taken at least 12 months of residential relocation (instead of 180 days in the main model); and iii) Stratification by the IP2011 deprivation index, focusing on the least and most deprived subpopulations.

Statistical significance was set at 5%, and all tests were two-tailed. All analyses were conducted in R version 4.2.2 (R Core Team, Vienna, Austria) using the *plm* package for fixed effects analyses (Croissant & Millo, 2008).

3. Results

Movers had, at baseline, median age of 4 years (ranging from 2 to 16 years); 19% were of foreigners, approximately 25% were in the most deprived areas at baseline. Compared to non-movers, movers had a higher proportion of foreigners and were more deprived at baseline (quintiles 4/5) (Supplementary Table 1). Between 59 and 67% moved to similar air pollution areas, 17–20% moved to less and 16–21% moved to more polluted areas (Table 1, Supplementary Table 2). For $PM_{2.5}$ only, those moving to more polluted areas were more deprived (quintiles 4/5) at baseline (43.8%) compared to those moving to less polluted areas (quintiles 4/5: 38.4%) (Table 1); small differences were observed in the other two exposure change categories (Supplementary Table 2). Median increases in air pollution in those who relocated to more polluted areas were 1.5, 4.5, 16.4 μg/m^3 for $PM_{2.5}$, PM_{10}, and NO_2, respectively (Table 1, Supplementary Table 2).

Adjusted fixed effects analyses show that residential relocation to more polluted areas for $PM_{2.5}$, PM_{10} and NO_2 was associated with an increase in zBMI (e.g. for children of average age in the study: β NO_2 = 0.10(95%CI 0.09; 0.12)). Moving to similar air pollution areas was associated with a reduced zBMI for all three pollutants (e.g. for children of average age in the study: β NO_2 = −0.03(95%CI -0.04; −0.02)). Moving to areas with less air pollution levels did not show significant association with follow-up zBMI (Table 2).

The interaction term between mean-centered age and air pollution area change was significant in all models. Associations were stronger for the younger ages compared to adolescence. For example, in children of primary school-age (6–11 years), increases in zBMI were observed among those moving to more polluted $PM_{2.5}$, PM_{10} and NO_2 areas (e.g. β NO_2 = 0.12(95%CI 0.09; 0.14)) and decreases in zBMI were observed among those moving to areas with similar air pollution levels for all air pollutants. In preschool-age children (2–5 years), moving to more polluted PM_{10} and NO_2 areas was associated with increases in zBMI, but no other associations were seen. No statistically significant associations were observed in adolescents (12–17 years) (Table 3).

Sensitivity analyses considering zBMI measurements at least 12 months after residential relocation showed that the previous associations of moving to more polluted areas with increases in zBMI were maintained for $PM_{2.5}$ and PM_{10}, but not for NO_2. Moving to similar air pollution areas were also associated with decreases in zBMI after 12 months for all air pollutants. For NO_2, those moving to less polluted areas showed statistically significant decreases in zBMI, however significant zBMI increases were observed for those moving to less polluted $PM_{2.5}$ and PM_{10} areas (Supplementary Table 3). In Supplementary Table 4, stratified analyses by the deprivation index at baseline showed that moving to more polluted areas increased zBMI regardless of baseline deprivation.

4. Discussion

In this large natural experiment study in Catalonia, we observed that

Table 1
Characteristics of the study population (total movers) and according to $PM_{2.5}$ air pollution area changes after residential relocation (N = 46,644).

	Total movers[a]	Air pollution area change		
		$PM_{2.5}$		
		Moving to a less polluted area	Moving to a similar area	Moving to a more polluted area
Sample size - n(%)	46,644 (100)	9,238 (19.8)	27,735 (59.5)	9,671 (20.7)
Age at baseline (years) - Md [IQR]	4.1 [2.4; 6.7]	4.1 [2.4; 6.7]	4.2 [2.5; 6.7]	4.2 [2.5; 6.9]
Sex - n(%)				
Female	22,576 (48.4)	4,484 (48.5)	13,404 (48.3)	4,688 (48.5)
Male	24,068 (51.6)	4,754 (51.5)	14,331 (51.7)	4,983 (51.5)
Nationality - n(%)				
Foreign	8,935 (19.2)	1,701 (18.4)	5,383 (19.4)	1,851 (19.1)
Spain	37,709 (80.8)	7537 (81.6)	22,352 (80.6)	7,820 (80.9)
Deprivation index at baseline[b] – n(%)				
Q1 (least deprived)	7,726 (16.9)	1,899 (20.9)	5,669 (20.8)	1,607 (16.9)
Q2	8,196 (17.9)	1,783 (19.6)	5,575 (20.5)	1,801 (18.9)
Q3	8,664 (18.9)	1,921 (21.1)	5,304 (19.5)	1,942 (20.4)
Q4	9,508 (20.7)	1,742 (19.1)	5,295 (19.4)	2,121 (22.3)
Q5 (most deprived)	11,750 (25.6)	1,752 (19.3)	5,390 (19.8)	2,043 (21.5)
zBMI at baseline - Md [IQR]	0.5 [-0.3; 1.3]	0.5 [-0.3; 1.3]	0.4 [-0.3; 1.3]	0.5 [-0.3; 1.3]
Weight status at baseline - n(%)[c]				
Underweight	571 (1.2)	100 (1.1)	364 (1.3)	107 (1.1)
Normal weight	36,324 (77.9)	7,140 (77.3)	21,618 (77.9)	7,566 (78.2)
Overweight	5,785 (12.4)	1,197 (13.0)	3,421 (12.3)	1,167 (12.1)
Obesity	3,964 (8.5)	801 (8.7)	2,332 (8.4)	831 (8.6)
Air pollution at baseline - Md [IQR]				
$PM_{2.5}$, ug/m^3	14.9 [13.8; 15.4]	15.2 [14.9; 15.8]	14.9 [13.7; 15.5]	14.0 [12.5; 14.8]
PM_{10}, ug/m^3	34.3 [30.6; 37.7]	35.6 [32.8; 38.4]	34.7 [30.7; 38.3]	32.2 [27.4; 35.6]
NO_2, ug/m^3	41.7 [26.2; 51.4]	44.3 [34.5; 52.4]	42.9 [26.1; 53.1]	32.9 [19.0; 45.4]
Changes in air pollution[d] – Md [IQR]		−1.5 [-3.3;-0.7]	0.0 [-0.3; 0.3]	1.5 [0.7; 3.2]
Population density at baseline - Md [IQR]	16,808.4 [3,550.3; 39,464.7]	19,278 [8,143; 37,255]	18,437 [3,778; 42,372]	9,535 [965; 33,598]
Time before moving (years) - Md [IQR]	2.7 [1.3; 5.2]	3.0 [1.5; 5.5]	2.5 [1.1; 4.9]	3.0 [1.5; 5.6]
Time after moving (years) - Md [IQR]	3.4 [1.7; 5.9]	3.2 [1.6; 5.7]	3.6 [1.8; 6.1]	3.2 [1.6; 5.6]

PM: Particulate matter; $PM_{2.5}$: PM < 2.5 μm; Md: Median, IQR: Interquartile range, zBMI: Body mass index z-scores, Q1-Q5: Deprivation index in quintiles 1 to 5. [a] Only those who moved once in the study period 2011–2018; [b] Social deprivation index based on the IP2011 deprivation index; [c] zBMI cut-offs based on the WHO Growth Charts (de Onis, 2007; World Health Organization (WHO) Multicentre Growth Reference Study World Health Organization Multicentre

Growth Reference Study Group, 2006); [d] After-before moving difference in μg/m^3.

Table 2
Associations between air pollution change after residential relocation and child/adolescent zBMI change at the average age in the study (N = 46,644).

Air pollution change (No. (%))	Adj. Model β (95%CI)
$PM_{2.5}$	
Moving to a less polluted area (9,238 (19.8))	0.009 (−0.006; 0.024)
Moving to a similar area (27,735 (59.5))	**−0.030 (-0.041; -0.019)**
Moving to a more polluted area (9,671 (20.7))	**0.059 (0.044; 0.074)**
PM_{10}	
Moving to a less polluted area (7,982 (17.1))	0.007 (−0.008; 0.023)
Moving to a similar area (31,362 (67.2))	**−0.027 (-0.037; -0.016)**
Moving to a more polluted area (7,300 (15.7))	**0.078 (0.061; 0.095)**
NO_2	
Moving to a less polluted area (8,082 (17.3))	−0.006 (−0.022; 0.010)
Moving to a similar area (30,980 (66.4))	**−0.031 (-0.041; -0.020)**
Moving to a more polluted area (7,582 (16.1))	**0.103 (0.087; 0.120)**

PM: Particulate matter, PM_{10}: PM < 10 μm, $PM_{2.5}$: PM < 2.5 μm, NO_2: Nitrogen dioxides, CI: Confidence intervals. Adj. model included population density, deprivation index IP2011, mean-centered age, plus an interaction term between mean-centered age*air pollution area change. Reported values represent the estimated effect of residential relocation for children of mean age. **Bold** highlights statistical significance ($p < 0.05$).

Table 3
Associations between air pollution change after residential relocation and child/adolescent zBMI, stratified by age-groups.

Air pollution change	Preschool-age (2-5 y) (N = 29,730) β (95%CI)	School-aged (6-11 y) (N = 15,782)	Adolescence (12-17 y) (N = 1,082)
$PM_{2.5}$			
Moving to a less polluted area	−0.001 (−0.021; 0.018)	0.004 (−0.019; 0.026)	−0.078 (−0.169; 0.013)
Moving to a similar area	−0.005 (−0.019; 0.009)	**−0.048 (-0.064; -0.032)**	0.062 (−0.003; 0.127)
Moving to a more polluted area	0.011 (−0.009; 0.032)	**0.067 (0.044; 0.090)**	−0.000 (−0.096; 0.096)
PM_{10}			
Moving to a less polluted area	−0.020 (−0.042; 0.001)	0.022 (−0.001; 0.045)	−0.009 (−0.105; 0.086)
Moving to a similar area	−0.002 (−0.016; 0.011)	**−0.050 (-0.066; -0.034)**	0.047 (−0.017; 0.110)
Moving to a more polluted area	**0.026 (0.002; 0.048)**	**0.084 (0.059; 0.109)**	−0.014 (−0.121; 0.093)
NO_2			
Moving to a less polluted area	−0.021 (−0.042; 0.000)	−0.011 (−0.034; 0.013)	−0.085 (−0.184; 0.014)
Moving to a similar area	−0.008 (−0.021; 0.006)	**−0.048 (-0.064; -0.033)**	0.047 (−0.016; 0.110)
Moving to a more polluted area	**0.048 (0.025; 0.070)**	**0.117 (0.092; 0.143)**	0.019 (−0.085; 0.123)

PM_{10}: PM < 10 μm, $PM_{2.5}$: PM < 2.5 μm, NO_2: Nitrogen dioxides, PM: Particulate matter, CI: Confidence intervals, y: years. Model adjusted for population density, IP2011 deprivation index, mean-centered age, plus an interaction term between mean-centered age*air pollution area change. Reported values represent the estimated effect of residential relocation for children of mean age in each group. **Bold** highlights statistical significance ($p < 0.05$).

increases in $PM_{2.5}$, PM_{10} and NO_2 due to residential relocation were associated with increases in zBMI among children and adolescents aged 2–17 years. We also found significant decreases in zBMI for those who moved to areas of similar air pollution, but not for those moving to less polluted areas. Associations were stronger in younger children than in adolescents.

Evidence has been inconsistent on the association between air pollution and weight-related outcomes in children. A recent systematic review concluded that there is a strong evidence of association between NO_2 and NO_x and childhood obesity, but evidence is still weak for PM_{10} and $PM_{2.5}$ (Malacarne et al., 2022). Traffic-related air pollution (such as NO_2 and NO_x) seem to have a stronger impact on childhood overweight compared to particulate matter ($PM_{2.5}$ and PM_{10}), which are driven to a lesser degree by local traffic (Bloemsma et al., 2019; Malacarne et al., 2022).

The biological mechanisms that link air pollution to weight gain are not fully understood, since several direct and indirect mechanisms may explain the association between the exposure to air pollution and excess weight. Animal studies have described that air pollution leads to visceral adipose tissue inflammation, hepatic lipid accumulation, decreased glucose utilization by skeletal muscles (Liu et al., 2014), and insulin resistance (Sun et al., 2009) in mice, which could all increase obesity risk. In humans, air pollution leads to oxidative stress and adipose tissue inflammation (Daiber et al., 2020), decreased utilization of glucose in skeletal muscle (Toledo-Corral et al., 2018), disruption of the endocrine system (Darbre, 2018), respiratory diseases and decreased lung function (Wang et al., 2019), changes in basal metabolism and appetite control of the central nervous system (McConnell et al., 2016), a higher risk of cardiovascular diseases (Bourdrel et al., 2017), among other adverse health impacts. When traffic and air pollution levels rise, families may also increase their sense of danger, leading to behavior changes (e.g. decrease of outdoor physical activities), which may increase weight (An et al., 2018a,b; Tainio et al., 2021). Unfortunately, we were not able to account for the effect of residential relocation on those behaviors. More longitudinal studies that take into account direct and indirect factors that could mediate the relation between air pollution and excess weight are necessary aiming to confirm the long-term impacts of air pollution.

To our knowledge, this is one of the first studies that used a "moving to health" (Drewnowski et al., 2019) natural experiment study design to explore effects of the environment on weight in a large longitudinal sample. Braun and colleagues used this study design to explore effects of moving on changes in walking, BMI and cardiometabolic risk in a sample of 1,000 middle-aged adults in the US, and have found that adults who moved to more walkable areas showed decreases in blood pressure and higher C-reactive protein, however not in BMI (Braun et al., 2016). Others have, nevertheless, found significant decreases in BMI of 700 adults who moved to more walkable US neighborhoods (Hirsch et al., 2014). Our study adds to this body of evidence examining the effects of air pollution on weight gain, with the focus on younger ages, using a natural experiment approach. We found that increases in air pollution exposure increased zBMI, however, we did not see significant decreases in zBMI after moving to less polluted areas. We suggest that this might be related to the baseline air pollution exposure. Reductions in air pollution levels seem to be less relevant for those who were already exposed to higher levels of air pollution, compared to those who were exposed to lower levels. As we have observed previously, the dose-response levels seem to be steeper at lower levels, so the sudden increase in those children moving to a higher air pollution level may have a much larger effect than the among children moving to a cleaner environment. Besides, we found that moving to similar air pollution areas was associated with decreases in zBMI. In our sample, the majority moved to similar air pollution areas, and a lower proportion moved to less/more polluted areas, as also seen in other European cohorts (Saucy et al., 2023). Also, it might be that these areas with similar air pollution levels are greener, more walkable and with greater availability of play areas for children. Lastly, the mere act of moving may be a stressful event and this might have affected child weight as well (Jelleyman & Spencer, 2008). There might be other weight-related factors (e.g. walkability, behavior change) that might explain the effects of moving to similar air pollution areas and that were not captured in the current study.

Age was found to modify associations between air pollution change and zBMI, with associations seen in younger age-groups (pre-school and primary school-age) and no statistically significant associations seen in adolescence. Children have a peak prevalence in overweight/obesity at school age (De Bont et al., 2020), including the “adiposity rebound” period at ages 5–6 (Koyama et al., 2014), which might also explain the age effect observed. In a recent systematic review, age also showed to play an important role in associations between road traffic noise, exposure to green spaces and urbanization and weight outcomes in children and adolescents (Malacarne et al., 2022). In addition, other studies have observed that the strength of association between air pollution exposures and weight varies along the different types of pollutants and ages (Shi et al., 2022), so in-depth studies need to be performed aiming to better comprehend this effect.

Even though the magnitude of the observed associations is small, impacts on global public health could be high. Based on the fact that the exposure to air pollution is very widespread and 56% of world’s population live in urban, more polluted, areas (approximately 4.45 billion people in 2021) (Worldbank, 2022), and childhood BMI is an important predictor of health consequences later in life (Geserick et al., 2018; Kumar & Kelly, 2017), even small associations between air pollution and child weight gain outcomes may have important consequences for population’s health (de Bont et al., 2021). The rate of urban population is expected to double by 2050, at which point nearly 7 out of 10 people will live in cities (Worldbank, 2022). This increase in urbanization means that more people will live in more polluted and less green environments, warranting the need to deepen the knowledge on how the urban environment affects population’s health. In addition, it is not clear how reversable are the effects of air pollution on health, since this depends on several factors, including the duration and intensity of exposure, individual susceptibility, and the specific health effects involved. Acute health effects of air pollution may be reversible, such as throat irritation, cough and nasal congestion, however air pollution can have long-lasting or even permanent consequences (Edwards et al., 2022).

Air pollution has been described in some studies to have enhanced effects in more deprived populations (Cakmak et al., 2016; de Bont et al., 2021), who may be more susceptible to the adverse health outcomes of such exposure, due to poverty, inadequate health access, poorer nutrition and inadequate life conditions (Adler & Stewart, 2010; Peled, 2011). However, in our study we did not find a greater effect on weight among the more deprived. The confounding role of socioeconomic status in the relation between air pollution and health outcomes is still unclear in Europe (Hajat et al., 2015; Saucy et al., 2023), where more deprived areas do not necessarily mean that these are also more polluted, as seen in the US (Hajat et al., 2015), for example. Is it important to consider the confounding effect of socioeconomic status when investigating the relation between air pollution and health, since it may affect individual exposure mitigation resources/capabilities, besides being a predictor of residential relocation in Europe (Saucy et al., 2023). Besides, the degree of exposure to air pollution and the impact of the built environment on one’s health may deepen health disparities, inequality and economic development of societies (Hajat et al., 2015).

Study strengths include the use of a natural experiment study design. Since changes in the urban environment often take place in a slow pace and incrementally (e.g. with increases in population density, build environment, etc.), the focus on subjects that change residential location and, in this sense, experience an environmental change in a short period of time, helps to provide evidence on the association between air pollution exposure and health outcomes. Also, the use of residential relocation is a way of exposure randomization, as individuals are unaware of the air pollution levels they are moving out or into (Edwards et al., 2022) and protects against bias due to unmeasured time-invariant confounders, as long as these have a constant effect over time (Knuiman et al., 2014). However, it is worth mentioning that if major changes occur due to residential relocation, with subjects moving to much less polluted and greener neighborhoods, behavioral risk factors may also change (such as outdoor physical activity) and these potential changes were not measured in the current study. The large sample size of movers and long follow-up period are also major strengths of this study. Besides, the repeated anthropometric measurements were performed using the same protocol by pediatric health professionals. Lastly, according to the Spanish National Statistics Institute, geographic mobility in Spain is frequent (Instituto Nacional de Estadística, 2022). The access to longitudinal data of health care users, like SIDIAP, enables the implementation of natural experiment study designs to study the impact of the environment on health (Drewnowski et al., 2019).

Our study also has some limitations. First, we may not have captured the total number of movers in the SIDIAP population, since some participants may not have notified the residential relocation to the health care centre. Second, the focus on residential relocation may be challenging, since moving may be a substantial and stressful event, affecting health and behaviors (Jelleyman & Spencer, 2008). Third, approximately 46% of movers were of the most deprived areas at baseline in this sample, which may have enhanced the risk of developing adverse health outcomes due to air pollution exposure in the first place. It is also worth mentioning that residential relocation may also lead to food environment changes and a greater availability of unhealthy food outlets are usually found in city centers, where also air pollution levels are higher. Furthermore, the use of electronic health records does not provide data on motivations for moving, which could reflect a shift in individual deprivation level, for which we could not control (Drewnowski et al., 2019). While our approach limits the impact of inter-individual differences in relocation trajectories, unmeasured time-varying confounding due to other factors, e.g. changes in behavioral preferences and attitudes in response to the new environment, could also still be present (Braun et al., 2016). Children who move, for example, to more walkable and safe neighborhoods, may have changed their physical activity habits. Many are the possible determinants of residential relocation; a recent study (Saucy et al., 2023) showed that in two European birth cohorts, families who moved had higher parental education and household socioeconomic status, and also tended to move to greener and less urban areas. Obesity is a multifactorial condition, with several biological and environmental factors with significant effects on energy intake and expenditure (González-Muniesa et al., 2017). The current study relied on available data registered in primary health care centers in Catalonia and these did not permit us to explore on within-person changes in weight-related behaviors, such as diet and physical activity. Within-person variability is accounted for in our models; however, these do not account for changes in behavior as a result of moving to the new environment. Regarding the assessment of air pollution levels, the LUR models were performed in 2009, and the study period was from 2011 to 2018. However, according to European studies, the spatial variation in air pollution remains stable over several years (Cesaroni et al., 2012; Fecht et al., 2016). Finally, it is important to mention that both indoor and outdoor air pollution have important health effects in the population, leading to millions of preventable deaths worldwide. In the current study, we did not have data on ambient air pollution of these children, so we had to rely on data of outdoor air pollution measured in each census tract. It is also important to highlight that a considerable proportion of indoor air pollution comes from outdoors (Amato et al., 2014). In addition to the assessment of air pollution at census tract level, the measurement of indoor air pollution, such as at schools where children spend most of the time (de Bont et al., 2019), would have increased the robustness of the estimations.

5. Conclusions

In the search for preventive solutions for child excess weight, researchers have focused on modifiable environmental characteristics. Changes in individual behaviors, in the community structure, lifestyle and built environment (Malacarne et al., 2022; Yang et al., 2021), and the exposure to certain chemicals, including air pollutants, have shown to be associated with childhood weight (de Bont et al., 2021; Wang et al., 2021) and should, in this sense, be the focus of community-level prevention strategies. This natural experiment focused on residential relocation suggest that increased levels of air pollution after residential relocation may lead to child weight gain and provides more evidence to support ongoing efforts to lower air pollution levels as well as community-level prevention strategies on childhood overweight and obesity.

Credit author statement

Sarah Warkentin: Conceptualization; Data curation; Formal analysis; Methodology; Writing – original draft. **Jeroen de Bont**: Conceptualization; Data curation; Writing – review & editing. **Alicia Abellan**: Writing – review & editing. **Andrea Pistillo**: Writing – review & editing. **Apolline Saucy**: Methodology; Writing – review & editing. **Marta Cirach**: Data curation; Writing – review & editing. **Mark Nieuwenhuijsen**: Data curation; Writing – review & editing. **Sara Khalid**: Writing – review & editing. **Xavier Basagaña**: Writing – review & editing. **Talita Duarte-Salles**: Conceptualization; Funding acquisition; Supervision; Writing – review & editing. **Martine Vrijheid**: Conceptualization; Methodology; Project administration; Funding acquisition; Supervision; Writing – review & editing.

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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

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2023.122217.

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