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Effect of residential relocation on environmental exposures in European cohorts: An exposome-wide approach

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ABSTRACT

Residential relocation is increasingly used as a natural experiment in epidemiological studies to assess the health impact of changes in environmental exposures. Since the likelihood of relocation can be influenced by individual characteristics that also influence health, studies may be biased if the predictors of relocation are not appropriately accounted for. Using data from Swedish and Dutch adults (SDPP, AMIGO), and birth cohorts (BAMSE, PIAMA), we investigated factors associated with relocation and changes in multiple environmental exposures across life stages.

We used logistic regression to identify baseline predictors of moving, including sociodemographic and household characteristics, health behaviors and health. We identified exposure clusters reflecting three domains of the urban exposome (air pollution, grey surface, and socioeconomic deprivation) and conducted multinomial logistic regression to identify predictors of exposome trajectories among movers.

On average, 7 % of the participants relocated each year. Before relocating, movers were consistently exposed to higher levels of air pollution than non-movers. Predictors of moving differed between the adult and birth cohorts, highlighting the importance of life stages. In the adult cohorts, moving was associated with younger age, smoking, and lower education and was independent of cardio-respiratory health indicators (hypertension, BMI, asthma, COPD). Contrary to adult cohorts, higher parental education and household socioeconomic position were associated with a higher probability of relocation in birth cohorts, alongside being the first child and living in a multi-unit dwelling. Among movers in all cohorts, those with a higher socioeconomic position at baseline were more likely to move towards healthier levels of the urban exposome.

We provide new insights into predictors of relocation and subsequent changes in multiple aspects of the urban exposome in four cohorts covering different life stages in Sweden and the Netherlands. These results inform strategies to limit bias due to residential self-selection in epidemiological studies using relocation as a natural experiment.

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1. Introduction

Residential relocation is a common life event which can create challenges in observational environmental epidemiological studies. Since the choice of a new residence is often influenced by several individual, health and socioeconomic characteristics (Bostanara et al., 2021; Mikolai & Kulu, 2018), relocation can exacerbate existing inequalities in environmental exposure distributions (Bivoltsis et al., 2020), their health effects, (Green et al., 2015) and lead to loss-to-follow-up (Hodgson et al., 2015). Observed exposure differences between population subgroups often reflect differences in socioeconomic position and individual preferences regarding where to live, leading to "residential self-selection", a source of bias in environmental epidemiological research (Heinen et al., 2018; Lamb et al., 2020).

Residential relocation can also be leveraged as a natural experiment to investigate the causal relationship between changes in living environments and health. This approach, originating from health economics, has become increasingly popular in environmental health research (Crane et al., 2020). For example, recent studies used residential mobility as a natural experiment to evaluate the causal impact of changes in diverse aspects of the living environment on health behaviors and health such as the association between neighborhood disadvantage and body weight (Rachele et al., 2018), walkability and hypertension (Chiu et al., 2016), and urbanicity and transport behavior (De Vos et al., 2018). Residential relocation has also been used as a way to "randomize" changes in air pollution concentrations, arguing that people are mostly unaware of the levels of particulate matter that they are moving into or out from (Chen et al., 2021; Edwards et al., 2022). While this last approach makes such studies particularly robust against confounding, the same reasoning may not apply to other environmental exposures such as green space, urbanicity or road traffic, which are likely to depend on individual preferences and critical life events (Fig. 1).

Therefore, understanding which characteristics influence both (i) residential relocation and (ii) the choice of the new residence is important to avoid potential bias in observational health research. Studies have identified several individual predictors of relocation including gender, age, ethnicity, and socioeconomic position (Falkingham et al., 2016; Miller et al., 2022). Specific life events have also been documented as predictors of relocation, including starting university, forming a new partnership, childbirth, change in employment, and adverse health events (Falkingham et al., 2016; Lovasi et al., 2014). Further, the predictors of residential relocation often vary by region and subgroups of the population (Bennett et al., 2022) and may change across genders (Falkingham et al., 2016) and over the life course (Morris et al., 2018). In a recent study investigating the joint impact of individual, social, and health characteristics on relocation, (Bennett et al., 2022) found that predictors of residential relocation differed between long- and short-distance moves, suggesting that many aspects of relocation choices remain to be understood. Despite an increasing body of research focusing on residential relocation, several aspects of residential relocation thus remain widely unknown, especially considering its influence on multiple environmental exposures. Overall, predictors of relocation are heterogenous and the reasons for different relocation trajectories (e.g. moving distance, change in individual characteristics, change in the living environment) require further research.

The exposome framework aims to consider the totality of environmental exposures experienced over the life course (Wild, 2012) and offers a unique opportunity to leverage large individual and environmental datasets for residential relocation studies. To address the gap in the literature regarding possible sources of bias constraining the use of residential relocation as a natural experiment to investigate the influence of changes in multiple environmental exposures on health, this study explores the predictors of moving behaviors and exposure trajectories in different age groups using two adult and two birth cohorts from the EXPANSE project (Exposome powered tools for healthy living in urban settings) (Vlaanderen et al., 2021). The findings from this study are expected to inform the possibility and means of using naturally-occurring residential relocation as a natural experiment in exposome research. Our objectives were:

(1) To identify the health, socioeconomic and behavioral determinants of residential relocation among adults and young children (0–4 years);
(2) To characterize urban exposome trajectories resulting from residential relocation;
(3) To identify determinants of urban exposome trajectories resulting from residential relocation.

2. Methods

2.1. Study population

We used two adult cohorts ("Stockholm Diabetes Prevention Programme" (SDPP), Sweden; "Occupational and Environmental Health Cohort Study" (AMIGO), the Netherlands) and two birth cohorts ("Children, Allergy, Milieu, Stockholm, Epidemiology" (BAMSE), Sweden; "Prevention and Incidence of Asthma and Mite Allergy" (PIAMA), the Netherlands) participating in the EXPANSE project. For SDPP, BAMSE and PIAMA, full residential histories (lists of consecutive residential locations with exact moving dates) were available from follow-up questionnaires and population registries. For AMIGO, residential locations were available at baseline and follow-up questionnaires, derived from population registry (mean follow-up time = 4 years, ranging from min. 3 to max. 5 years). Cohorts' information, residential histories and exclusions are summarized in Table 1.

SDPP aims to study the importance of hereditary, individual and environmental determinants on impaired glucose tolerance, diabetes and related morbidities like obesity and high blood pressure (Ljungman et al., 2019). It is a population-based survey in which 3,128 men and

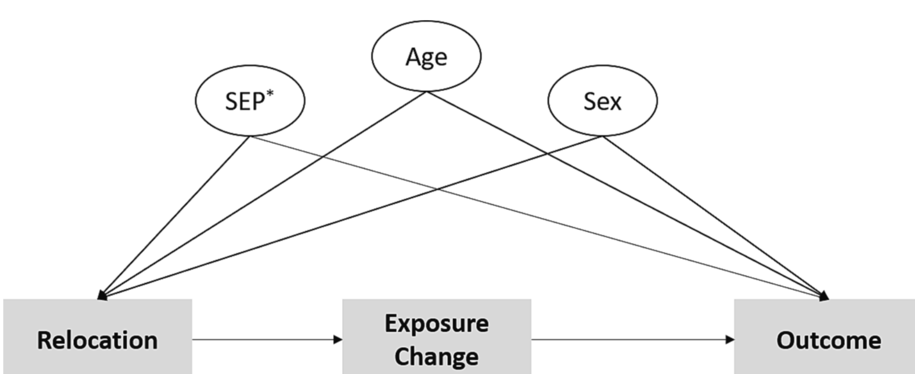

Fig. 1. DAG (Directed Acyclic Graph) displaying the causal association between a change in exposure due to relocation and health outcomes as typically used in relocation studies (relocation as a natural experiment). Since naturally-occurring relocation is the result of an individual, professional or life choice and potentially influenced by various individual and socioeconomic factors (as opposed to an external real-life intervention) the association may be biased in the absence of adequate adjustment. * SEP: socioeconomic position.

Table 1

Description of the four cohorts included in the study, including origin, size, and source of the residential histories. In the adult cohorts, exclusions are due to missing geocodes at baseline or follow-up. In the birth cohorts, where addresses and relocation events were collected during follow-up visits, loss to follow-up can also lead to exclusion from the study.

	SDPP	AMIGO	BAMSE	PIAMA
Cohort type	Adult cohort	Adult cohort	Birth cohort	Birth cohort
Country	Sweden	The Netherlands	Sweden	The Netherlands
# persons included	7903	14,538	3718	3494
# persons excluded*	none	268	371	469
Temporal extent (T0 to T1)	1992–2002	2011–2016	1994–2000	1994–2001
Ages covered (years)	35–60	30–70	0–4	0–4
Source of the residential histories	Population registry	Population registry	Collected at follow-up questionnaire.	Collected at follow-up questionnaire.
Availability of individual addresses and relocation dates and potential selection bias	Individual relocation events and dates available throughout the whole follow-up period	Addresses available at T0 and T1, independently of follow-up status. Exact relocation dates are not available.	Individual addresses and relocation dates available. Relocation events are not collected when participants are lost to follow-up.	Individual addresses and relocation dates available. Relocation events are not collected when participants are lost to follow-up.

* Summary statistics of the excluded individuals are described in Supplementary Table S1.

4,821 women (between the ages 35–56) from five municipalities of Stockholm County Council were screened between the years 1992–1998. Approximately half (53 %) had a first- or second-degree relative with a history of diabetes, and the remaining recruits were matched on age and sex. All participants were free of diabetes at recruitment. A follow-up study was conducted about 10 years later where 76.2 % of the men and 69.1 % of women responded.

AMIGO is a sample of 14,829 working-age adults in the Netherlands selected between 31 and 65 years of age at baseline. It is a representative sample of the adult population of working age in the Netherlands created to investigate occupation and environmental health from a ‘multidisciplinary and life-course perspective’(Slottje et al., 2014). Recruitment happened between 2011 and 2012, where individual, socioeconomic, behavioural and health characteristics were collected. A second wave of data was collected about 4 years after baseline (min. 3, max. 5) with about 50 % response rate; participants in the second wave had higher socio-economic position than the baseline population.

PIAMA is a birth cohort from the Netherlands, that was set up 1) to investigate the effect of mite-allergen avoidance on the incidence of childhood asthma and allergy; and 2) to assess lifestyle and environmental risk factors for childhood asthma and allergy (Wijga et al., 2014). The baseline study population includes 3,963 children born in 1996 and 1997. Information on parental education, ethnicity and allergy history was collected by parental-completed questionnaires during the child’s first year of life. Health questionnaires were implemented in 13 waves (at 3 months, annually from 1 to 8 years, at 11 years, 14 years, 17 years, and 20 years). At each wave, data on the residential address were collected and questionnaires were administered. Clinical examinations were performed at ages 1, 4, 8, 12 and 16 years.

BAMSE is an ongoing longitudinal, population-based prospective birth cohort including 4,089 children born between 1994 and 1996 in Stockholm, Sweden, designed to study risk factors for asthma, allergic diseases and lung function in childhood. Questionnaires on respiratory symptoms and medication were administered regularly during childhood (years 1, 2, 4, 8, 16 and 24 years) as well as medical examinations including spirometry and blood samples at ages 8, 16 and 24. Baseline information including household characteristics, socioeconomic status and residential history was available at baseline and re-assessed several times during follow-up (Wang et al., 2021).

2.2. Inclusion criteria

To investigate the predictors of relocation and exposome trajectories, the four datasets were restricted to participants’ addresses at T0, defined as the cohort’s baseline questionnaire for adult cohorts and at birth for the birth cohorts, and after the first 4 years of follow-up in all cohorts, defined as T1. In AMIGO, T1 was defined as the time of the first follow-up questionnaire, administered from 3 to 5 years after baseline. “Movers” were defined as those who relocated at least once between T0 and T1 (Fig. 2). We considered all cohort participants who completed the baseline questionnaire (7,903 persons for SDPP, 14,806 for AMIGO, 4,089 for BAMSE and 3,963 for PIAMA) and with valid, geocoded addresses at T0 and T1 (7,903 persons for SDPP, 14,538 for AMIGO 3,724 for BAMSE, and 3,494 for PIAMA). In addition to addresses at T0 and T1, we used all available relocation events for the full extent of the cohorts’ follow-up times (20, 20 and 24 years respectively) to calculate annual relocation rates in SDPP, PIAMA and BAMSE (descriptive statistics).

2.3. Urban exposome

To characterize the urban exposome across all four cohorts, we selected a large range of modelled exposure surfaces across all study sites with high spatial resolution available for the EXPANSE project. Environmental exposure data were available as raster surfaces. Individual exposure estimates for all study participants were obtained by extracting exposure surface raster values at home addresses at T0 and T1. Ambient air pollution surfaces were available for selected years between 2000 and 2010 from the ELAPSE project (de Hoogh et al., 2018). Built environment data (green, grey and blue space) were developed in the framework of the EXPANSE project with exposure surfaces available in 2019, 2015 and 2010 respectively. In addition, country-specific area-level variables (population density, degree of urbanization, unemployment rate, proportion of high and low income, proportion of high and low education) were available from national databases for SDPP, PIAMA and AMIGO. Given the limited temporal availability for some exposure surfaces and to isolate the influence of relocation on changes in exposure as well as remove the influence of time trends on exposure change, we assigned the same exposure surface to individual addresses at T0 and T1. When exposure surfaces were available for several years, we selected surfaces for the years that were closest to the cohorts’ baseline period, which ranged between 1992 and 2012 in the four cohorts (highlighted in bold in Table 2). All exposures and sources are summarized in Table 2.

2.4. Covariate and outcome data

To obtain a broad understanding of the individual predictors of relocation, all analyses considered (1) sociodemographic (2) cardiorespiratory health and (3) health behavior characteristics at T0 for the adult cohorts; and (1) sociodemographic, (2) household and (3) parental health characteristics at T0 for the birth cohorts (Table 3). Whenever necessary, variables were recategorized for definitions to match across cohorts. In the adult cohorts, baseline socio-demographic characteristics were sex, age centered at the mean of 50 years and reported for 10-years increases, education (low / medium / high), marital status (married or living with partner yes / no) and employment status (employed /

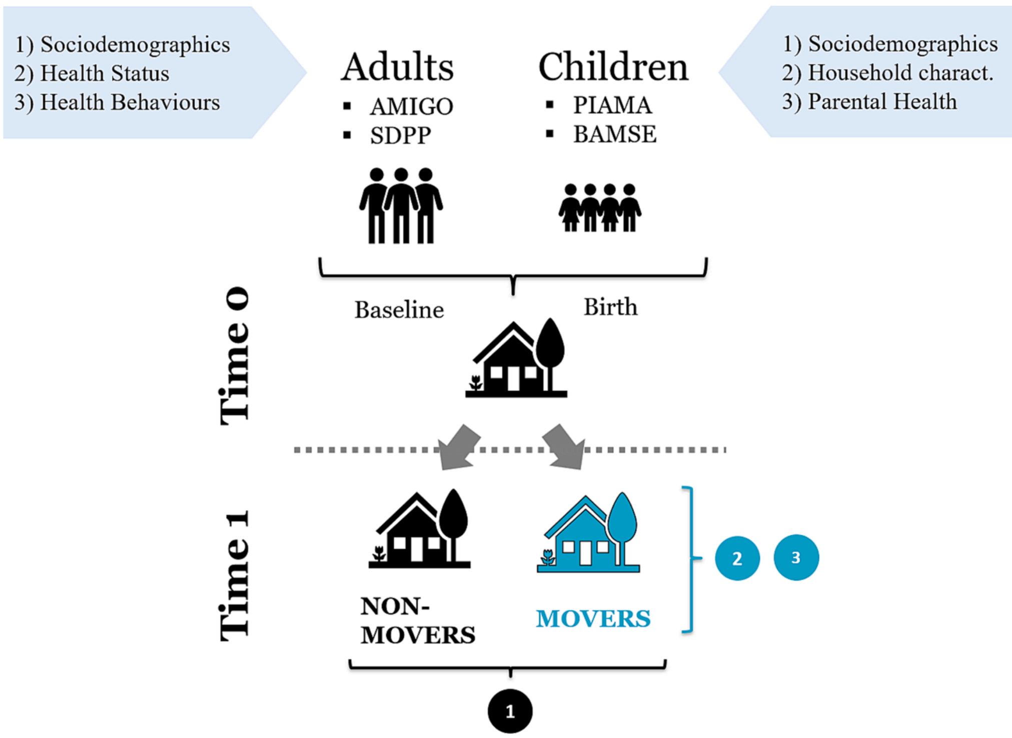

Fig. 2. Overview of the study design: 2 birth and 2 adult cohorts were followed from baseline or birth (T0) and 4 years of follow-up (T1). Those who changed residence between T0 and T1 were defined as "movers". Objective (1) focused on the differences between movers and non-movers (indicated in black) and Objectives (2) and (3) focused on movers only (indicated in blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

housewife or -husband / unemployed / retired). Cardiorespiratory health status included hypertension and body mass index (BMI, available for both adult cohorts), asthma (yes / no), as well as COPD and chronic heart condition (yes / no, available in AMIGO). Cardiorespiratory health behaviors included smoking status (never smoker / ex-smoker / current smoker, both cohorts), alcohol consumption (never / ever / current, both cohorts) and physical activity (low / moderate / regular / frequent, available in SDPP) at T0. For the birth cohorts, sociodemographic characteristics included sex, nationality (recategorized as "national" if the child has the cohorts' country nationality or "not national" otherwise) and highest parental education (low / medium / high). Household characteristics were available in BAMSE: siblings (yes / no), dwelling type (single-unit / multi-unit) and household socioeconomic position (SEP) categorized as low (blue collar) / medium (lower white and white collar) / high (higher white collar). Parental allergy was available in PIAMA (any of asthma or hay fever; yes / no).

2.5. Statistical analyses

The three main objectives were addressed using distinct statistical approaches, as described below. For all regression strategies (logistic, linear and multinomial models), separate analyses were conducted for each cohort, followed by pooled models by cohort type (adults and birth cohorts separately) restricted to variables available in all cohorts and including cohort as a fixed effect. For all regression analyses, the models were built in three steps, with M1 referring to models adjusting for all sociodemographics; M2 to models adjusting for sociodemographics (M1) and health behaviours (adult cohorts) or household characteristics (birth cohorts); M3 to models adjusting for sociodemographics (M1) and health status. No models combined health behavior and health outcomes, since most health outcomes considered in this study are expected to be on the pathway between health behavior and relocation choices. The modelling approach is summarized in Table 3.

2.5.1. Descriptive statistics

We identified all moving events occurring during the full follow-up time of SDPP, BAMSE and PIAMA and calculated yearly relocation rates for these three cohorts. In AMIGO, where addresses were available at baseline and follow-up, we calculated the average yearly relocation rate based on the percentage of individuals who changed location between these two times. Contrary to the other cohorts, multiple moves are not captured in AMIGO, which may lead to an underestimation of the annual relocation rate in this cohort. Individual characteristics and exposure distributions were reported at home locations before (T0) and after moving (T1) for movers and non-movers separately.

2.5.2. Objective 1: Determinants of residential relocation

To identify determinants of residential relocation, we conducted multivariable logistic regression to investigate the associations of individual characteristics with the probability of residential relocation (yes / no) in each cohort and in adults and birth cohorts separately.

2.5.3. Objective 2: Identifying trajectories of the urban exposome

To characterize trajectories in the urban exposome resulting from residential relocation, we considered the following domains: **air pollution** (nitrogen dioxide [NO_2], black carbon [BC], particulate matter with diameter < 2.5 μg/m^3 [$PM_{2.5}$], ozone [O_3]), **grey surface** (Impervious surface, NDVI, distance to water) and **socioeconomic deprivation** (cohort-specific area-level socioeconomic indicators included average income, unemployment rate, percent low and high education, percent below social minimum). To make all our analyses comparable and harmonize the range of the different variables, all exposures were rescaled using the following formula: ($X_{rescaled}$= (X-X_{min})/ X_{max}-X_{min}). Rescaled values ranged between 0 and 1 and preserved the direction of the exposure changes (e.g. moving to higher exposure levels will result in a positive $\Delta exp_{rescaled}$). Within each domain, we applied a k-means clustering approach based on the Hartigan and Wong algorithm (Hartigan and Wong, 1979) to identify three cluster levels of rescaled exposures. The number of clusters was chosen to be consistent across cohorts and domains and was visually validated using elbow plots (Sammouda & El-Zaart, 2021). We then identified individual urban exposome trajectories from T0 to T1, defined as relocating into a similar (reference trajectory), lower ("healthy" trajectory) or higher ("hazardous" trajectory) cluster level. Given the large variations in exposure

Table 2
List of exposures available for this analysis. The exposure years used for these analyses are highlighted in bold.

Exposure	year	Resolution	Source
Physico-chemical environment*			
NO_2	**2000**–2005-2010	100 × 100 *m*	ELAPSE
PM2.5	**2010**	100 × 100 *m*	ELAPSE
BC	**2010**	100 × 100 *m*	ELAPSE
O3	**2000**–2005-2010	100 × 100 *m*	ELAPSE
Green, grey and blue space**			
NDVI (green space)	**2019**	250 × 250 *m*	EXPANSE
Impervious surface (grey space)	**2015**	250 × 250 *m*	EXPANSE
Distance to nearest blue space (incl. sea, water, canals)	**2010**	250 × 250 *m*	EXPANSE
Socioeconomic environment***			
% Below social minimum	**2015**	Neighborhood	CBS
% Low income (lowest 40 % pop.)	**2015**	Neighborhood	Statistics Netherlands (CBS)
% High income (highest 20 % pop.)	**2015**	Neighborhood	Statistics Netherlands (CBS)
Mean income	**2011**	Neighborhood	Statistics Sweden
Unemployment rate	**2011**	Neighborhood	Statistics Sweden
% Low education	**2011**	Neighborhood	Statistics Sweden

* Ambient air pollution surfaces were developed as part of the ELAPSE project using a land use regression approach. The data used for the models include air pollution monitoring data, satellite observations, dispersion models estimates, land use and traffic data (de Hoogh et al., 2018).
** Built environment variables were developed specifically for the EXPANSE project. NDVI (Normalized Difference Vegetation Index) were derived from the Vegetation Indices (MOD13Q1) product of the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) with 250 m × 250 m resolution (Didan, 2015). Distance to the nearest blue space was assessed using the EU-Hydro map developed by the CLMS (Copernicus Land Monitoring Service, 2019). Grey (i.e. built-up) spaces were characterized using imperviousness density (IMD) maps (Copernicus Land Monitoring Service, 2020).
*** Exposures of the socioeconomic environment were collected for each cohort separately according to availability. For the two Dutch cohorts (AMIGO and PIAMA) the data were at the neighborhood-level ("Buurt") from Statistics Netherlands (Central Bureau of Statistics CBS, 2022). In the Netherlands, neighborhoods are defined as "part of a municipality dominated by a given type of land use or buildings. For instance: industrial area, residential area with high-rise or low-rise buildings" (Central Bureau of Statistics CBS, 2022). For SDPP, the socio-economic data were at the neighborhood-level from the Swedish National Statistical Office (Statistics Sweden, 2000). In Sweden, neighborhoods are defined as "Small Area Market Statistics" (SAMS) which refer to "the smallest areal units in a system of geographical co-ordinates areas in Stockholm and 9,281 SAMS areas in the rest of Sweden. The boundaries of SAMS are drawn to include similar type of housing construction in an area and hence similar or fairly homogeneous socio-economic strata of residents in the SAMS areas" (Bajekal et al., 2016).

levels in the different cohorts, rescaling and clustering were performed separately for each cohort. As a result, only trajectories but not absolute cluster values can be compared across cohorts.

2.5.4. Objective 3: Determinants of changes in the urban exposome after residential relocation

Among movers, we conducted multivariable linear regression to investigate the association between baseline individual characteristics and exposure changes between T0 and T1 ($\Delta exp_{rescaled}$) in all European-wide exposures. Separate models were fitted for each rescaled exposure as the dependent variable. In addition, we estimated the associations

Table 3
Summary of modelling steps to identify the predictors of residential relocation, exposure change and cluster trajectories in adult and birth cohorts separately. Y represents the outcome of interest (respectively mover (binary), Δexp (continuous) and cluster trajectory (ordered categorical)) and f(Y) is the respective link function. Variables not uniformly available throughout a cohort type are displayed in italics. "Cohort" was included as a fixed-effect in the pooled analyses based on both adult and both birth cohorts respectively. The multinomial logistic models (cluster trajectories) contained cluster level at T0 as an additional explanatory variable (not shown).

Model	Adult cohorts	Birth cohorts
M1	**Sociodemographic Characteristicsf** $(Y) = \beta_0 + \beta_1 age + \beta_2 sex + \beta_3 married + \beta_4 education + \beta_5 occupation + \beta_6 Cohort$	**Sociodemographic Characteristicsf** $(Y) = \beta_0 + \beta_1 sex + \beta_2 national + \beta_3 parent.educ. + \beta_4 Cohort$
M2	**M1 + Cardiorespiratory Health Behavioursf** $(Y) = \beta_0 + \beta_1 age + \beta_2 sex + \beta_3 married + \beta_4 education + \beta_5 occupation + \beta_6 smoking + \beta_7 \textit{phys.act.} + \beta_8 Cohort$	**M1 + Household Characteristicsf** $(Y) = \beta_0 + \beta_1 sex + \beta_2 national + \beta_3 parent.educ. + \beta_4 \textit{housetype} + \beta_5 \textit{siblings} + \beta_6 \textit{household.SEP} + \beta_7 Cohort$
M3	**M1 + Cardiorespiratory Health Statusf** $(Y) = \beta_0 + \beta_1 age + \beta_2 sex + \beta_3 married + \beta_4 education + \beta_5 occupation + \beta_6 hypertension + \beta_7 BMI + \beta_8 asthma + \beta_9 \textit{COPD} + \beta_{10} \textit{cardiovascular} + \beta_{11} Cohort$	**M1 + Parent Healthf** $(Y) = \beta_0 + \beta_1 sex + \beta_2 national + \beta_3 parent.educ. + \beta_4 \textit{parent.allergy} + \beta_5 Cohort$

between baseline individual characteristics and the previously identified urban exposome trajectories, for each cohort and cohort type (adults and birth cohorts separately) using multinomial logistic regression. To account for the influence of baseline exposure levels, models were adjusted for cluster levels (low, medium or high) at T0.

3. Results

3.1. Descriptive statistics

Residential relocation was frequent in all 4 cohorts with an average moving rate of 7 % per year. BAMSE had the highest moving rate (12.8 % per year on average). While moving rates remained mainly constant over time in SDPP, most relocation events in the birth cohorts happened during the first years after birth and during young adulthood. Individual moves for the three cohorts with full residential history are presented in Supplementary Figure S1. Overall, moving was more frequent in birth cohorts (34 % and 54 % movers between T0 and T1 in PIAMA and BAMSE, respectively) compared to adult cohorts (18 % and 8 % in SDPP and AMIGO respectively). Most of the relocations happened over short distances between T0 and T1 (mean distances = 17 km in PIAMA, 27 km in BAMSE, 16 km in SDPP, and 11 km in AMIGO). In SDPP, 70 % of moves were within the same region, and 21 % were within the same neighborhood. In PIAMA, 60 % of moves were within the same city and 27 % were within the same neighborhood. In BAMSE, 47 % of moves were within the same city.

In the adult cohorts, residential relocation was less frequent for married and older people (mean age of movers at T0 = 45 and 47 years in SDPP and AMIGO respectively, against 49 and 51 years for non-movers); in AMIGO, retirees were less likely to relocate compared to employed individuals. In both cohorts, the proportion of smokers was significantly higher among movers compared to non-movers. Among the cardiorespiratory health variables, hypertension was more common among non-movers. Other health outcomes were equally distributed across both groups (Table 4). In both birth cohorts, movers had higher parental education and household socio-economic position compared to non-movers. Moving was also more frequent in children living in single dwellings compared to multi-unit dwellings (Table 5).

Table 4
Distribution of individual characteristics among movers and non-movers (during the first 4 years of follow-up) in the SDPP and AMIGO adult cohorts. P-values for the difference between movers and non-movers were calculated using the Wald-test (univariable regression).

Individual characteristics	**SDPP**			**AMIGO**		
	Non-movers	**Movers**	**p**	**Non-movers**	**Movers**	**P**
N (%)	6441 (82)	1462 (18)		13,322 (90)	1216 (10)	
SOCIODEMOCGRAPHIC CHARACTERISTICS						
Age (mean, SD)	49.0 (3.8)	45.0 (3.2)	<0.001	50.9 (9.2)	46.9 (10.2)	<0.001
Sex (female; n, %)	3898 (60.5)	911 (62.3)	0.215	7410 (55.6)	715 (58.8)	0.035
married or living with partner (n, %)	5501 (85.4)	1068 (73.1)	<0.001	10,890 (81.7)	800 (65.8)	<0.001
Education (n, %)			0.034			0.565
Low	1968 (30.6)	462 (31.6)		4068 (30.5)	352 (28.9)	
Medium	2372 (36.8)	579 (39.6)		4168 (31.3)	377 (31.0)	
High	1918 (29.8)	388 (26.5)		5078 (38.1)	486 (40.0)	
Occupation (n, %)			0.114			<0.001
Employed	5851 (90.8)	1303 (89.1)		9558 (71.7)	906 (74.5)	
Housewife/husband	55 (0.9)	19 (1.3)		1107 (8.3)	65 (5.3)	
Unemployed	357 (5.5)	85 (5.8)		312 (2.3)	37 (3.0)	
Retired	157 (2.4)	47 (3.2)		1248 (9.4)	82 (6.7)	
Other or missing	21 (0.3)	8 (0.5)		1097 (8.2)	126 (10.4)	
CARDIORESPIRATORY HEALTH BEHAVIOURS						
Smoking status (n, %)			<0.001			<0.001
Never smoker	2463 (38.2)	471 (32.2)		6112 (45.9)	521 (42.8)	
Current smoker	1630 (25.3)	458 (31.3)		2003 (15.0)	259 (21.3)	
Ex-smoker	2344 (36.4)	531 (36.3)		5187 (38.9)	433 (35.6)	
Physical activity (n, %)			0.280			
Sedentary	683 (10.6)	183 (12.5)		–	–	
Moderate	3545 (55.0)	789 (54.0)		–	–	
Regular	1702 (26.4)	384 (26.3)		–	–	
Frequent regular	504 (7.8)	105 (7.2)		–	–	
CARDIORESPIRATORY HEALTH STATUS						
Hypertension (n %)	1601 (24.9)	296 (20.2)	<0.001	3110 (23.3)	235 (19.3)	0.003
BMI (mean, SD)	25.7 (4.0)2.55 (0.40)0.050	25.5 (4.0)	0.050	26.1 (4.4)	25.8 (4.3)	0.051
Cardiovasc. disease (n, %)	–	–		1205 (9.0)	102 (8.4)	0.388
COPD (n, %)	–	–		497 (3.7)	38 (3.1)	0.247
Asthma = 1 (n, %)	0 (0.0)	0 (0.0)		1081 (8.1)	115 (9.5)	0.084

Table 5
Distribution of individual characteristics among movers and non-movers (during the first 4-years of follow-up) in the BAMSE and PIAMA birth cohorts. P-values for the difference between movers and non-movers were calculated using the Wald-test (univariable regression).

Individual characteristics	**BAMSE**			**PIAMA**		
	Non-movers	**Movers**	**p**	**Non-movers**	**Movers**	**P**
N (%)	1693 (46)	2025 (54)		2297 (66)	1197 (34)	
SOCIODEMOCGRAPHIC CHARACTERISTICS						
Sex (female; n, %)	857 (50.6)	1022 (50.4)	0.929	1080 (47.0)	603 (50.4)	0.160
Has country's nationality (n, %)	1238 (73.1)	1580 (77.9)	<0.001	2235 (97.3)	1147 (95.8)	0.034
Parents Education (n, %)			0.156			<0.001
Low	48 (2.8)	46 (2.3)		288 (12.5)	128 (10.7)	
Medium	763 (45.1)	879 (43.4)		864 (37.6)	396 (33.1)	
High	878 (51.9)	1101 (54.3)		1115 (48.5)	639 (53.4)	
HOUSEHOLD CHARACTERISTICS						
House Type (n, %)			<0.001			
Multi-unit dwelling	1225 (72.4)	1842 (90.9)		–	–	
Single-unit dwelling	468 (27.6)	183 (9.0)		–	–	
Other	0 (0.0)	2 (0.1)		–	–	
Siblings = yes (n, %)	983 (58.1)	807 (39.8)	<0.001	–	–	
Household SEP (n, %)			0.068			
Low	328 (19.4)	330 (16.3)		–	–	
Medium	737 (43.5)	894 (44.1)		–	–	
High	621 (36.7)	797 (39.3)		–	–	
CARDIORESPIRATORY HEALTH STATUS (PARENTS)						
Parents' allergy (*n*, %)	–	–		0.41 (0.49)	0.42 (0.49)	0.731

The distributions of urban exposures between movers and non-movers differed between the two adult cohorts. Before moving (T0), movers in SDPP were living in areas with higher levels of air pollution (NO_2, $PM_{2.5}$ and BC) and more urbanized areas (higher impervious surface, lower NDVI, higher percentage of people living in cities) compared to non-movers. Differences in exposure levels between movers and non-movers increased after residential relocation at T1. In AMIGO, exposure levels were mostly comparable between movers and non-movers, both at T0 and T1 (Supplementary Table S2). In the two birth cohorts, movers had higher concentrations of air pollutants (NO_2, $PM_{2.5}$ and BC) at T0 than non-movers, but these differences decreased after moving (T1) (Supplementary Table S3).

3.2. *Objective 1: Determinants of residential relocation*

The sociodemographic predictors of residential relocation (M1) in the adult cohorts included being non-married, retired, younger age, and lower education (Fig. 3). Being a current or ex-smoker was the only

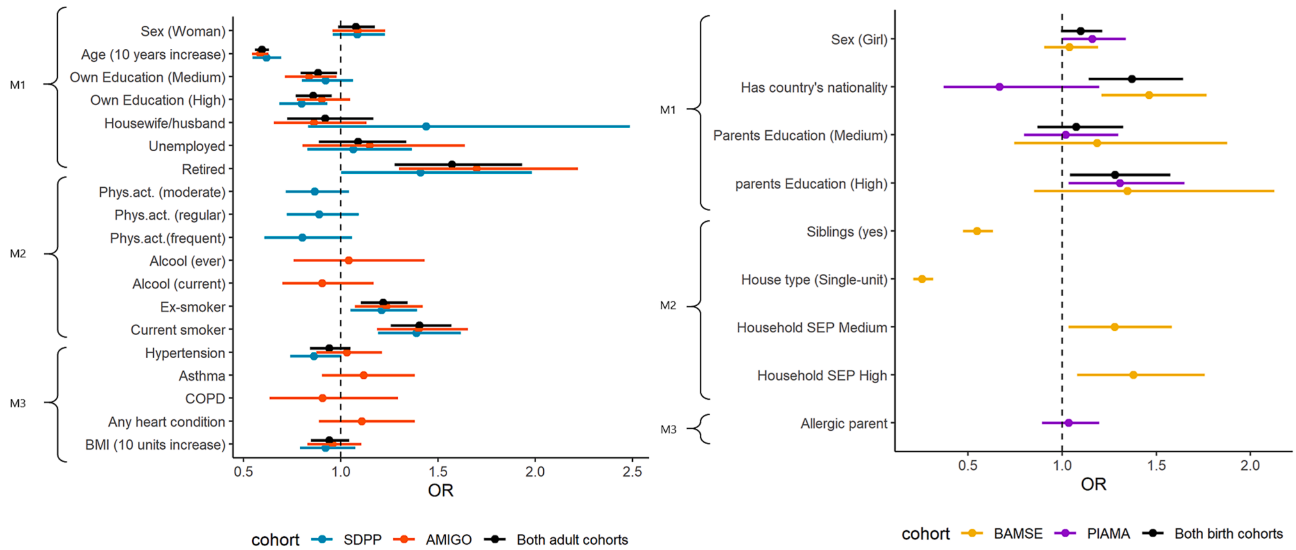

Fig. 3. Odds ratios and 95 % confidence intervals from multi-variable logistic regression for residential relocation in association with baseline socio-demographics (M1), health behavior (M2) and health status (M3) in the two adult cohorts (left panel) and with baseline socio-demographics (M1), household characteristics (M2) and parental health (M3) in the two birth cohorts (right panel). OR > 1 indicates increased odds of relocation.

health behavior associated with an increased probability of relocation in adult cohorts (M2). When adjusting for sociodemographic characteristics (M3), none of the health conditions (asthma, COPD, BMI, hypertension and chronic cardiovascular disease) remained significantly associated with the probability of residential relocation. Contrary to the adult cohorts, higher SEP was associated with an increased probability

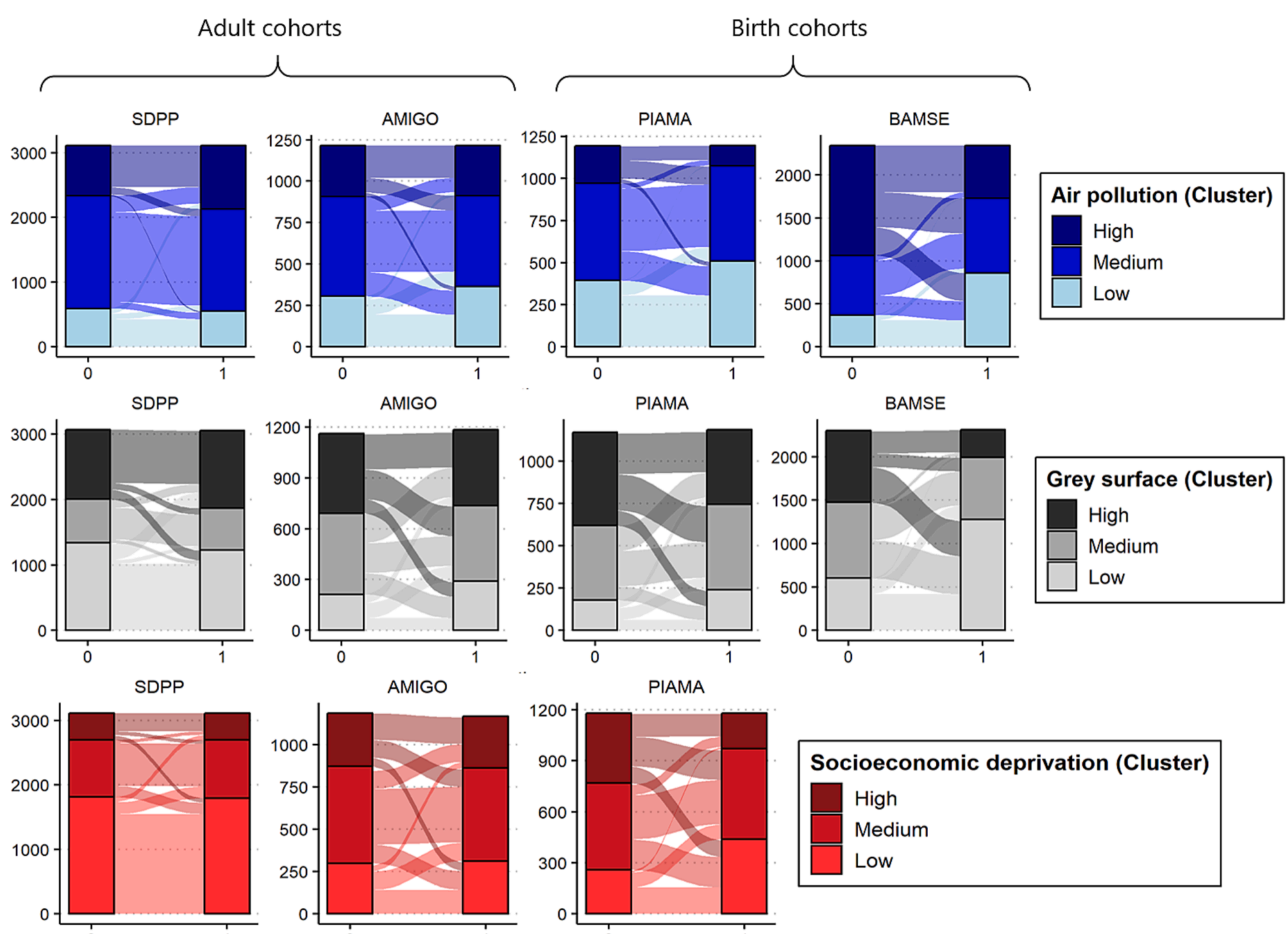

Fig. 4. Changes in cluster levels for three domains of the urban exposome among movers between T0 and T1: air pollution (top panel), grey surface (middle panel) and socioeconomic deprivation (bottom panel). Lower cluster levels represent lower levels of air pollution, grey surface and socioeconomic deprivation. Note: clusters were built separately for each cohort and cluster distributions at given times cannot be compared across cohorts.

of residential relocation in the birth cohorts (M1). However, the effect of the child having the nationality of the country of the cohort was in different directions for the two birth cohorts. In BAMSE, children with older siblings and children who lived in individual houses were less likely to move compared to only/ first-born children and those living in multi-unit dwellings (M2). Parental allergic status was not associated with the probability of relocation in PIAMA (M3).

3.3. Objective 2: Identifying trajectories of the urban exposome

Pearson's correlations across urban exposures ranged between −95 % (NO_2 and O_3) and 90 % (NO_2 and BC, Supplementary Figure S2). For all three domains of the urban exposome, the k-means clustering approach identified three groups, which we labelled as "low", "medium" and "high" hazard environments. For air pollution, higher cluster values contained higher NO_2, $PM_{2.5}$ and BC and lower O_3 concentrations (Supplementary Figure S3). For grey surface, higher cluster values represented increased levels of impervious surface (grey space) and lower levels of NDVI (green space). On average, the lowest levels of the grey surface cluster (lower grey, higher green space) were associated with a shorter distance to water but the distance to water's contribution to the domain's clustering was minimal (Supplementary Figure S3). For the socioeconomic deprivation domain, higher cluster values represented higher socioeconomic deprivation (lower income and education, higher unemployment rate in SDPP; lower proportion of high income, higher proportion of low income and people living below the social minimum in PIAMA and AMIGO; Supplementary Figure S4).

Changes in individual cluster levels over time (T0 and T1) for air pollution, grey surface and social deprivation are displayed in Fig. 4. Overall, most movers relocated within the same exposure cluster level for all three domains of the urban exposome (same cluster = reference trajectory). Among participants of the adult cohorts, movers equally relocated to higher and lower levels of air pollution, grey surface, and socioeconomic deprivation. In the birth cohorts, the proportion of participants relocating to lower air pollution, lower grey surface, and lower socioeconomic deprivation ("healthy" trajectories) was greater than the proportion relocating towards higher levels ("hazardous" trajectories).

3.4. Objective 3: Determinants of urban exposome trajectories due to relocation

3.4.1. Change in individual exposures after relocation

The levels of NO_2 and impervious surface were lower in SDPP compared to the three other cohorts. On average, the two Dutch cohorts (PIAMA and AMIGO) had higher $PM_{2.5}$ and BC levels than the Swedish cohorts (BAMSE and SDPP; Supplementary Figure S6, panel A). Similar to the exposome cluster trajectories, the changes in individual exposure levels between baseline and follow-up in the two adult cohorts were symmetrical (i.e. equal number of participants moving from low to high exposure as moving from high to low). In the birth cohorts, young children tended to move to lower NO_2, and higher NDVI areas at T1 compared to T0 (Supplementary Figure S6, Panel B). The predictors of individual exposure change (results from the linear regression models) are described in detail in Supplementary Figure S7. In addition to individual characteristics, urban exposure levels at T0 were important predictors of individual exposure changes upon moving (Supplementary Figure S8).

3.4.2. Determinants of exposome cluster trajectories

In adult cohorts, cluster-based multinomial logistic regression models (Fig. 5) showed an association between age, marital status and education with the three domains of the urban exposome (M1). Higher education was associated with moving to higher levels of air pollution and lower levels of grey surface and socioeconomic deprivation. Older and married individuals tended to relocate to areas with comparable cluster levels. If they changed clusters, married people were more likely to relocate to lower ("healthier") levels of all three domains, and older people to areas with increased air pollution. Smoking was associated with increased odds of changing their exposure to all domains of the urban exposome and especially towards increased socioeconomic deprivation (M2). There was only an inconsistent association between health status and urban exposome trajectories (M3). Overall, the

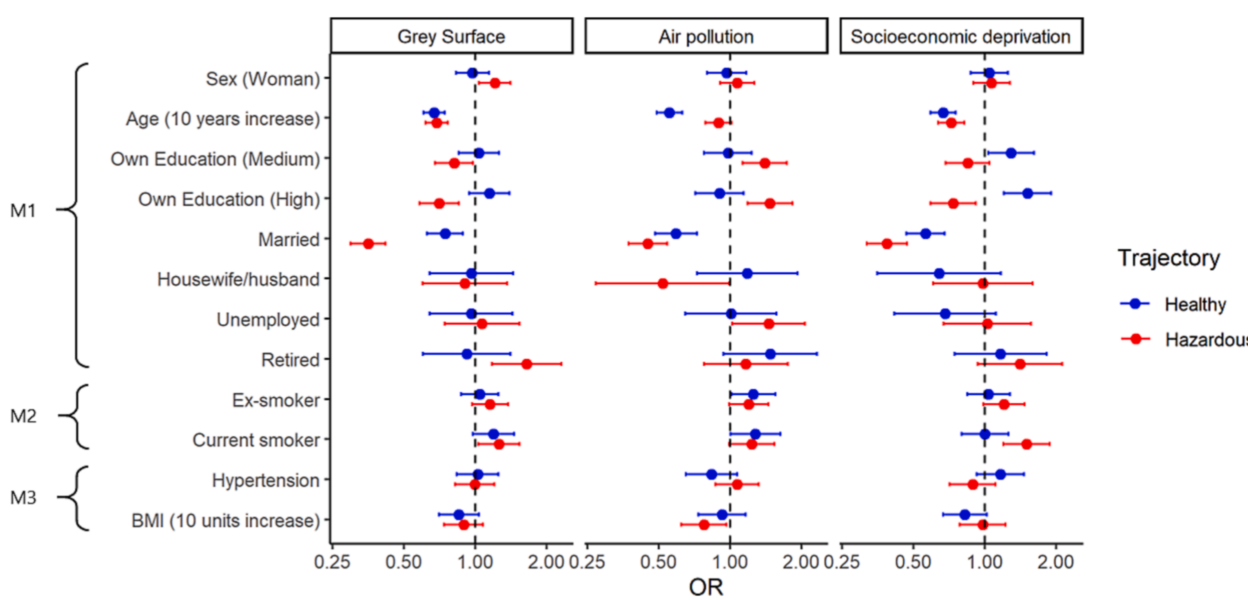

Fig. 5. Odds ratio and 95 % confidence intervals for different cluster trajectories (multinomial logistic regression) in adult cohorts for grey surface, air pollution, and socioeconomic deprivation trajectories. Moving into a similar cluster level was chosen as the reference. Changes from lower to higher clusters ('hazardous trajectory') are displayed in red. Changes from higher to lower clusters ('healthier trajectory') are displayed in blue. OR > 1 indicates increased odds for hazardous (red) and healthy (blue) trajectories, respectively. M1 includes sociodemographic characteristics; M2 sociodemographic characteristics and health behavior, and M3 sociodemographic characteristics and health. Note: this figure displays only variables available in both adult cohorts. More detailed and cohort-specific results are available in Supplementary Figure S9 and Supplementary Table S4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

associations between individual characteristics and urban exposome trajectories were consistent across both cohorts (Supplementary Figure S9).

In birth cohorts (M1), having the country's nationality was consistently associated with relocating towards lower ("healthier") cluster levels for both air pollution and built surface in both cohorts (Fig. 6). On average, higher parental education was associated with moving to lower ("healthier") grey surface and socioeconomic deprivation (PIAMA only). Children living in single-unit dwellings were more likely to relocate into areas with similar levels of all three domains of the urban exposome (M2). Similar to adult cohorts, children from families with higher socioeconomic positions relocated into lower grey surface cluster values, but not traffic-related pollution (Supplementary Figure S10). Parental allergy was not associated with urban exposome trajectories upon moving (M3).

4. Discussion

Our analyses based on data from four European cohorts resulted in several key findings. First, residential relocation was frequent (7 % of cohort participants moved each year) and varied across age groups and cohort types. Second, considering three domains of the urban exposome (air pollution, grey surface and socioeconomic deprivation), we could classify the urban exposome into three hazard levels (low/medium/high) and identify urban exposome trajectories for all movers. Finally, we found that moving trajectories differed across cohort types and were affected by various sociodemographic, behavior, and household characteristics. Health status at baseline was found to play a minimum impact on residential trajectories. Overall, more privileged groups of the population (higher individual SEP) moved towards healthier areas with regards to most domains of the urban exposome, thus exacerbating existing environmental health disparities.

As part of objective 1 investigating the determinants of residential relocation, we found that sociodemographic and household characteristics (e.g. age, marital and co-habitation status in adults and birth order and housing type in children) were among the most relevant predictors of relocation, consistent with existing evidence. For example, previous studies found that relocation was associated with female gender, young compared to older adulthood, non-white ethnicity, and lower socioeconomic position (Falkingham et al., 2016; Miller et al., 2022). Among the cardio-respiratory health endpoints and health behaviors investigated, only smoking was significantly associated with increased odds of relocation. While poorer health has been reported to be associated with residential relocation (Falkingham et al., 2016; Green et al., 2015), these associations disappeared after adjusting for age and education as previously described elsewhere (Geronimus et al., 2014). Similarly, Bennett et al. found that demographics were more important to predict residential mobility than other individual characteristics, including health status (Bennett et al., 2022; Hansen, 1987). This phenomenon is depicted in Fig. 7. In addition, we observed a significant association between retirement status and relocation in models adjusted for age, consistent with other evidence that sudden life changes such as changing jobs, employment, or getting married are important drivers of relocation (Whybrow et al., 2021). The role of life events and family situation for relocation (Coulter & Scott, 2015; Evandrou et al., 2010; Geronimus et al., 2014) was also visible in our findings from the birth cohorts. Namely, household characteristics were found to be among the most important predictors of relocation in birth cohorts. For example, children living in apartments were more likely to relocate than those living in single-unit houses. Those who had an older sibling were less likely to relocate than first-born children, highlighting the importance of starting a family as a trigger for residential relocation (Evandrou et al., 2010).

As part of objective 2 aiming to identify urban exposome trajectories in movers, we classified a range of environmental exposures into increasing hazard levels with regards to three domains of the urban exposome (air pollution, grey surface and socioeconomic deprivation). Given the inverse correlation between O_3 and the other air pollutants,

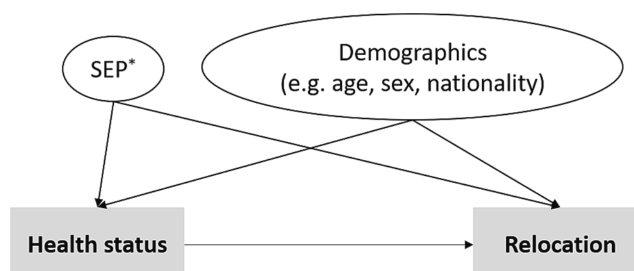

Fig. 7. DAG (Directed Acyclic Graph) displaying the causal association between health status and the probability of residential relocation, suggesting that the crude association between health and relocation is confounded by sociodemographic characteristics that impact health and the probability of relocation. *SEP: socioeconomic position.

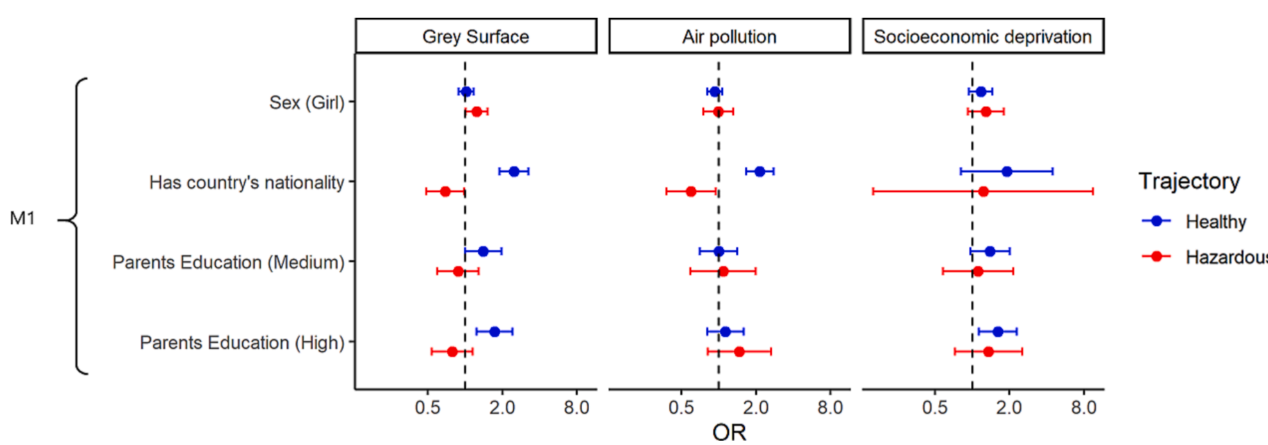

Fig. 6. Odds ratio for different cluster trajectories (multinomial logistic regression) in both birth cohorts for the grey surface, air pollution, and socioeconomic deprivation trajectories (PIAMA only). Moving into a similar cluster level was chosen as the reference. Changes from lower to higher clusters ('hazardous trajectory') displayed in red. Changes from higher to lower clusters ('healthier trajectory') displayed in blue. OR > 1 indicates increased odds for hazardous (red) and healthy (blue) trajectories, respectively. M1 includes sociodemographic characteristics; M2 sociodemographic and household characteristics; M3 sociodemographic characteristics and parental health. Note: this figure displays only variables available in both adult cohorts. More detailed and cohort-specific results are available in Supplementary Figure S10 and supplementary Table S5. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the highest hazard air pollution cluster contains lower ozone levels, which may limit our ability to investigate the joint impact of O_3 and other air pollutants in health studies. Similarly, greenness and impervious surface only reflect part of the complexity of the built urban environment and its impact on health (Münzel et al., 2021). This classification may mask structural differences in highly urbanized environments, such as access to public transport, healthcare, walkable environments (Lowe et al., 2014; Paulo Dos Anjos Souza Barbosa et al., 2019) or sports facilities (Lee et al., 2016). The categorization of the urban exposome domains into hazard levels is therefore context-specific and may vary across countries and health outcomes of interest. Nevertheless, our clustering approach by domains allowed us to reduce the number of exposure variables, with limited correlation between each other. We identified exposome trajectories for all movers in our study that can be used in future multiple-exposure epidemiological studies. Similar to previous research (Kivimäki et al., 2021), we observed that people mostly relocated into similar levels of the three domains of the urban exposome. Nevertheless, "healthy" trajectories (i.e. moving to lower cluster levels) were more common in the birth cohorts compared to the adult cohorts, which can reflect the preferences of young parents for greener, less urban areas but also selection towards lower area-level deprivation levels in both birth cohorts (53 % high parental education in birth cohorts vs 35 % high education in adult cohorts).

Our findings in relation to objective 3 investigating the predictors of exposome trajectories in movers indicate that relocation trajectories were largely influenced by sociodemographic and household characteristics, with consistent patterns across cohorts. In adult cohorts, age, marital status and education were the most relevant predictors of exposome trajectories. Namely, higher SEP was associated with a reduction in grey space and socioeconomic deprivation, but an increase in air pollution. This apparent contradiction could reflect the fact that socioeconomic deprivation and grey space are visible characteristics of the living environment and therefore have a larger impact on the choice of residence (Coulter & Scott, 2015) whereas air pollution is less visible (Awad et al., 2019; Edwards et al., 2022) and less influential in the choice of a new residential location. In some cases, areas with higher pollution levels such as urban centers may even be considered more desired areas (Richardson et al., 2013). Married and older people presented stable relocation behaviors. Apart from moving less often (objective 1), they showed a preference for comparable areas with regards to most aspects of the urban exposome when relocating. On the contrary, smokers were more likely to relocate to areas with different levels of air pollution and grey surface (both higher and lower). In addition, smokers, non-married people and those with lower education were more likely to move to areas with increased socioeconomic deprivation, worsening previous environmental exposure disparities (Bivoltsis et al., 2020; Green et al., 2015). It has been shown that young adults tend to move from cities to suburban areas, sometimes followed by a return to more urbanized areas when getting older to be closer to family or health facilities (Whybrow et al., 2021). This transition is in line with our findings, where older age was associated with moving to areas with similar or higher levels of air pollution. Similar to our findings from objective 1, we showed that health status played a minimal role in the different exposome trajectories across all cohorts. Nevertheless, in one of the adult cohorts (AMIGO), people with asthma and pre-existing cardiovascular disease were at higher odds of relocating to areas with increased air pollution, grey space and socioeconomic deprivation. It is not clear whether this residential preference is a direct consequence of the disease itself (e.g. moving closer to health facilities, reduced financial resources) or is driven by further, unmeasured socioeconomic characteristics. Our conclusions from the adult cohorts were also supported by our findings in the birth cohort with area-level socioeconomic data (PIAMA) in which higher parental education and country's nationality were associated with a reduction in area-level socioeconomic deprivation upon relocation. Similarly, having the country's nationality was associated with "healthy" trajectories with regard to air pollution and built surface in both birth cohorts.

Second, we found that exposure trajectories depend on a range of sociodemographic and household characteristics, which are often difficult to fully capture in statistical models. Since relocation does not occur randomly, the choice of counterfactuals in relocation studies is critical to limit the risk of bias due to residential self-selection. Typical counterfactuals include (1) non-movers with similar baseline characteristics (Mccormack et al., 2017); (2) other movers with different exposure trajectories (Awad et al., 2019); or (3) both movers and non-movers (Powell-Wiley et al., 2015). In agreement with our findings, restricting the analyses to movers (approach 2) can help reduce structural differences between movers and non-movers. In a few cases where environmental exposures showed little association with individual characteristics after relocation (e.g. $PM_{2.5}$ and BC), the assumption that changes in air pollution exposure due to relocation are mostly unaffected by individual characteristics (Awad et al., 2019; Chen et al., 2021) is likely to hold, in which case comparing movers with different relocation trajectories is subject to minimum bias. However, our results suggest that changes in most aspects of the urban environment upon relocation are tightly linked to individual characteristics suggesting that this approach is likely not sufficient to prevent confounding by residential self-selection and baseline exposure. Since socio-demographics are important predictors of relocation, further aspects of SEP not captured by our indicators and generally difficult to measure may also be relevant predictors of moving trajectories and affect estimated associations. As a result, residential relocation studies may require the use of further causal inference approaches to help resolve this issue, including self-matched designs (Gunasekara et al., 2014; Mostofsky et al., 2018) or difference-in-difference studies (Strumpf et al., 2017). If adequately designed, these two approaches can limit confounding by unmeasured non-varying characteristics and are also compatible with further adjustment for baseline exposure levels, which were important predictors of exposome trajectories in our study. Additional strategies aiming to make study and control groups more comparable such as inverse-probability matching and weighting (Keogh et al., 2018) and stratification by zip-code or baseline exposures (Awad et al., 2019) are also helpful to reduce the risk of residual confounding. Changes in time-varying factors such as occupation, income or family situation may lead to bias if not accounted for.

Our study has several strengths and innovations. First, the inclusion of four cohorts from two countries and age groups contributed to a larger dataset and findings with better external validity for other European populations. These data allowed us to investigate differences in predictors of relocation and exposure change across different life stages from early life in the birth cohorts (0–4 years), to adulthood, including working and retirement ages in the adult cohorts. In the birth cohorts, SEP and health characteristics were collected from the parents, which also offers information on residential preferences during parenthood. Second, to the best of our knowledge, this is the first study to systematically identify the determinants of exposure change following residential relocation, considering a wide range of urban exposures simultaneously. We did this using high-resolution exposure data harmonized across Europe developed in the EXPANSE project. Third, the trajectory clustering approach presented several advantages; it allowed us to reduce the dimensions of the multiple environmental exposures affected by relocation and to assess the contribution of individual characteristics on well-defined domains of the urban exposome and it allowed for adjustment on baseline exposome groups, reducing bias due to residential self-selection.

Several limitations should be acknowledged. This study focused on baseline predictors of relocation and relocation trajectories. Our data did not contain detailed information on changes in job, income or SEP over time, which are also likely to affect relocation behaviors. While several life events are known to trigger relocation, more research is needed to understand to what extent they may influence exposure trajectories including repeated measurement of individual characteristics over time. Other individual characteristics such as race/ethnicity were not considered. Further, the different exposure surfaces varied in their yearly availabilities, leading to differences between the time of relocation and the year for which exposure surfaces were available. However, our study focused on exposure changes in space due to relocation. Since spatial variability is expected to be greater compared to slow changes over time at a given location, possible time trends in exposure are unlikely to affect our findings. This assumption is supported by the coherence of our results across cohorts covering various years. Built environment and ambient pollution exposure surfaces were available at a high spatial resolution and accurately represent various aspects of the exposome lived at the home location. They do not cover exposures experienced away from home, such as work or school. While using multiple cohorts has many advantages, data were not fully harmonized across cohorts and data on socioeconomic deprivation was available only for three of the four study cohorts. Similarly, all cohorts were from Northern Europe and may not be reflective of determinants of relocation and exposure trajectories across other European regions.

5. Conclusion

Several individual characteristics including age, marital status, smoking and education were associated with the probability of residential relocation. Among movers, different exposure trajectories were observed in adult and birth cohorts, suggesting that life stage largely affects both moving behaviors and the choice of a new residential location. In our results adjusting for baseline exposures, more privileged subgroups of the population were more likely to relocate to healthier areas with regards to different domains of the urban exposome (built surface and socioeconomic deprivation). Our results provide a richer understanding of predictors of relocation and subsequent changes in multiple environmental exposures which can inform the study design of natural experiments using relocation as a source of exposure variability.

CRediT authorship contribution statement

Apolline Saucy: Conceptualization, Methodology, Formal analysis, Investigation, Writing – review & editing. **Ulrike Gehring:** Investigation, Writing – original draft, Writing – review & editing. **Sergio Olmos:** Writing – review & editing, Methodology. **Cyrille Delpierre:** Methodology, Writing – review & editing. **Jeroen de Bont:** Writing – review & editing. **Olena Gruzieva:** Investigation, Writing – review & editing. **Kees de Hoogh:** Investigation, Writing – review & editing. **Anke Huss:** Investigation, Writing – review & editing. **Petter Ljungman:** Investigation, Writing – review & editing. **Erik Melén:** Investigation, Writing – review & editing, Funding acquisition. **Åsa Persson:** Writing – review & editing. **Inka Pieterson:** Writing – review & editing. **Marjan Tewis:** Investigation, Writing – review & editing. **Zhebin Yu:** Investigation, Writing – review & editing. **Roel Vermeulen:** Conceptualization, Writing – review & editing, Project administration, Funding acquisition. **Jelle Vlaanderen:** Conceptualization, Writing – review & editing, Project administration, Funding acquisition. **Cathryn Tonne:** Conceptualization, Writing – review & editing, Methodology, Writing – original draft, Supervision, Funding acquisition.

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 material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2023.107849.

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