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A good move for health?

Analyzing urban exposure trajectories of residential relocation and mental health in populations in Bradford

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Abstract: Residential relocation can be leveraged as a natural experiment. This study examined the changes in environmental exposures due to residential relocation in two samples of within-city movers in Bradford (UK); 2089 residents (66% women, mean [SD] age, 47.80 [19.88] years) with preexisting common mental disorders-related prescriptions and 12,699 residents (60% women, mean [SD] age, 42.47 [17.40] years) without the same prescriptions at baseline (January–April 2021). Study data were extracted from National Health Service health records. The outcome was the presence of an active prescription for anxiolytics or antidepressants (yes/no) 1 year after relocation (January–April 2022). Change scores were calculated for several exposures, including the normalized difference vegetation index, distance decay to green spaces, coarse (PM_{10}) and fine particulate matter ($PM_{2.5}$), and nitrogen dioxide (NO_2) at pre- and postmove addresses. Logistic regression models were used for each change score exposure, adjusting for covariates selected using a direct acyclic graph validated against the data. Participants without prescriptions at baseline were likely to relocate to less green and less polluted areas compared with those with preexisting medication. A total of 15% of participants without prescriptions at baseline had an active prescription at follow-up. For these, increases in normalized difference vegetation index were associated with lower odds of having active prescriptions at follow-up [OR (odds ratio) = 0.93 (95% confidence interval [CI] = 0.88, 0.98), $P = 0.007$], whereas increases in $PM_{2.5}$ [OR = 1.1 (95% CI = 1.04, 1.16), $P < 0.001$] and PM_{10} [OR = 1.12 (95% CI = 1.06–1.19), $P < 0.001$] concentrations were associated with higher odds. Changes in environmental exposures due to residential relocation showed an influence on mental health only for those participants without active prescriptions in the baseline.

Keywords: Antidepressants; Anxiolytics; Geographic information systems; DAG; Air pollution; Green spaces

Introduction

Common mental disorders (CMDs) such as anxiety and depression affect up to 580 million people across the globe.[1] They are the leading cause of years spent living with disability and generate huge societal burdens from care costs to lost economic productivity. Socio-economically vulnerable populations, such as people living in poverty, facing unemployment or with low educational attainment, along with ethnic minority groups, and those living in deprived areas, are at higher risk of developing CMD.[2–4] This might be caused by the cumulative burden of chronic stress from financial insecurity, stigma, poorer work conditions, and lower access to social and healthcare support.[4] Anxiolytics and antidepressants are the usual pharmacological treatment options for CMD.

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Environmental determinants of mental health and residential mobility

A growing evidence points to the importance of environmental factors in promoting good mental health.[5] Previous studies have analyzed the associations between residential greenness or air pollution with CMD.[6–10] Plausible mechanisms behind such associations are related to lifestyle factors (e.g., physical activity or social cohesion), and inflammatory, oxidative, and neurotransmission-related impacts on the brain.[11,12] Part of this evidence has been compiled in recent systematic reviews.[11,13,14]

What this study adds?

This study contributes to the literatures on the environmental determinants of mental health and environmental justice by analyzing data from a diverse, multiethnic, and highly deprived population. To summarize, we found that residents with active medication prescriptions for common mental disorders were more likely to move to areas of worse environmental quality. Besides, we saw that changes in residential greenness and air pollution were linked to the onset of poor mental health problems.

However, not all population groups are equally exposed to these environmental burdens. Environmental injustice denotes the unequal distribution of environmental exposures that disproportionately affect certain population groups, increasing their exposure to harmful factors while limiting their access to beneficial environmental features.[15] This inequity might heighten the risk of already vulnerable groups and may exacerbate social inequalities in mental health.[16] For instance, current literature shows that people living in lower socioeconomic status (SES) areas are exposed to lower residential greenness levels, lower availability of green spaces, and higher levels of pollutants.[17–22] However, this pattern is not always consistent.[23,24] Environmental justice is usually conceptualized in static terms. This is, at any given moment, vulnerable populations within a city or region may reside in areas of poorer environmental quality. However, environmental (in)justice may also impact people's lives over time.

We know that people move for various reasons, which may include marital or job status changes, the death of loved ones or family changes such as the birth of a child.[25,26] In a recently published study compiling information from four Northern European birth and adult cohorts, the authors found that residential relocation was more frequently observed in nonmarried, retired, younger, and low-educated adults.[27] Other studies have shown opposite trends, such as the work by Heo and colleagues,[28] who followed a sample of pregnant women residing in New York and saw that residential movers were those with higher educational attainment and income.

Since environmental burdens may be associated with health outcomes, moving to areas with fewer burdens may positively impact health. Conversely, relocating to areas of poorer environmental quality may have the opposite effect, as suggested by Saucy et al.[27] Most movers in that study relocated to areas with similar levels of air pollution and for movers participating in the birth cohorts included in that study, those with higher education and having the study country's nationality were more likely to move to areas of improved environmental quality. Similarly, a study conducted in the USA used census information to track residential moves of older populations in southern states to see how relocation affected exposure to heat, extreme weather events, and air quality.[29] They found that the older the person, the higher the odds of moving to areas more exposed to heat and that those belonging to ethnic minority groups were more likely to move to areas with higher number of extreme weather events and poorer air quality. Finally, another study conducted in the US informed about the environmental implications of moving to lower SES neighborhoods within the moving to opportunity for Fair Housing Program.[30]

The epidemiology of relocation

Changes in environmental exposures due to residential moves can be leveraged to study how the environment affects human health by conducting natural experiments, which allow researchers to address questions that would be impractical, unrealistic, or even unethical if approached through planned research.[31–34] Most of the available evidence about the environmental determinants of health comes from cross-sectional studies, which do not allow for direct inference of causality. In the words of Rachele and colleagues[35] (see also Pedde and Adar[36]), relocation studies provide a strong basis to infer causation given that pre–postmove comparisons are controlled for individual observed and unobserved covariates that do not change over time. Besides, these sorts of studies help with developing a spatio-temporal approach to add the temporal/life course perspective to the place and health literature.[37] Apart from measuring changes in exposures, residential moves might also explain changes in health outcomes given the disruption of daily life and social interactions that ensue. Some works have documented that the number of moves is related to health outcomes, both during childhood and adulthood.[38,39] More specifically, these works showed that a higher number of moves was related to poorer health outcomes (i.e. vaccination rates during childhood and lower reported physical and mental health scores).

Few studies have explored the impact of changes in environmental stressors as a result of residential relocation on mental health. For instance, two recently published studies explored how changes in air pollution or walkability impacted the body mass index of children and adults, 180 days and 2 years after moving, respectively.[34,35] Changes in air pollution levels have also been studied in relation to respiratory outcomes, pregnancy morbidity, or mortality.[40] A limited number of works have specifically focused on mental health outcomes. The authors of a study using data from the British Household Panel Survey did not observe any statistically significant effect of changes in residential greenness due to residential moves on self-reported mental health.[41] Similar results were obtained in a study conducted in the Netherlands.[42] Tunstall and colleagues[43,44] used a composite measure of area socio-economic status, concentrations of air pollutants (e.g., PM_{10} or NO_2), and distance to industrial facilities. They found no effects of changes in said measure on postmove mental health. These studies on mental health relied on self-reported mental health outcomes, and those by Tunstall and colleagues, for the reasons explained above, did not estimate the specific effects of air pollutants. A recent study using UK Biobank data found that participants that moved from a lower to a higher $PM_{2.5}$ or PM_{10} polluted area increased the odds of being diagnosed with mental and behavioral disorders.[45] However, moving to areas of lower pollutant concentration did not show protective effects. Therefore, our study will contribute to this specific field because we used health records data to operationalize residents' mental health and compiled various measures of residential greenness and air pollutants.

Study aims

In this study, we sought to contribute to a better understanding of the interrelations between residential mobility, environmental exposures (i.e. residential greenness and air pollution), and the prescriptions for anxiolytics and antidepressants in the city of Bradford, UK. First, we aimed to explore whether movers with preexisting prescriptions were more or less likely to move to healthier environments. Second, we wanted to analyze whether changes in environmental exposures due to residential relocation were associated with the prescription duration for those participants with preexisting conditions—and the potential onset of prescriptions for those without. We expected increases in residential greenness metrics having protective effects on mental health and the opposite for air pollution metrics.

Methods

Study setting and sample of participants

According to the mid-2023 census by the Office for National Statistics, Bradford is home to 560,200 people in West Yorkshire, northern England and hosts a young, diverse and multiethnic community; 53% of the population identifies as White British,

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whereas citizens of Pakistani, Indian, and Bangladeshi ethnicities account for 30% of the population. It is the 13th most deprived local authority in England, with 32% of the population among the most deprived decile in the country. The central districts of the city are the most deprived and also have higher air and noise pollution levels and lower availability of green spaces than nondeprived areas.[46]

Our resident address and health data came from the Connected Bradford Whole System Data Linkage Accelerator (Connected Bradford Platform, CB hereafter), which contains information from 800,000 individuals residing in the city in the last 40 years.[47] This platform combines, among others, primary care data from general practices, community care data (including mental health, school nurse, and health visitor interactions) and secondary care data from acute hospitals, Yorkshire Ambulance Service, and Electronic Patient Records. Relevant to this study, the platform also contains a comprehensive set of urban environmental exposure metrics (e.g., air pollution or residential greenness).

From the CB platform, we extracted data on National Health Service patients who resided in Bradford during a baseline period (January–April 2021) and moved to another location in the city in the same period.

Study variables

Urban environmental exposures

We included five residential greenness and air pollution metrics to characterize participants' pre- and postmove residential settings. These are described in detail elsewhere.[48]

Residential greenness

The extent to which the residential environment was green was measured with two complementary variables: the normalized difference vegetation index (NDVI) and distance decay to major green spaces (>2 ha). NDVI measures the density of green vegetation captured in satellite imagery, and ranges from −1 to +1, with values closer to +1 indicating higher levels of greenness, while values near 0 indicate little to no vegetation, and negative values indicate nonvegetated surfaces, such as built-up surfaces. Cloud-free satellite images were obtained from the USGS Landsat 8 product for the year 2021.[49] Individual NDVI values were expressed as the mean value within a 300-m straight-line buffer radius around the participants' residential address.[50]

We also used the Ordnance Survey Open Greenspace dataset to calculate the distance between participants' houses and the entrance points of the following greenspace classifications with an area of at least 2 ha: public parks or gardens, allotments or community growing spaces, cemeteries, play spaces, religious grounds, bowling greens, golf courses, other sports facilities, playing fields, and tennis courts through the OS street, and urban path network (Ordnance Survey).[51,52] We then calculated a distance decay weighted count for each participant, using an exponential distance decay function with a decay parameter of 0.007, which converges to near zero at a 1-km distance (or after a 12-minute walk). Higher distance decay scores indicate greater green space availability.

Air pollution

Following previous studies, we used UK emissions data from the Department for Environment, Food and Rural Affairs, which features a 1 km × 1 km resolution. We used this data to calculate annual average levels of PM_{10}, $PM_{2.5}$, and NO_x in 300-m straight-line buffers around participants' residential address locations expressed in μg/m^3.[53]

Mental health

We obtained data on the prescription of antidepressants and anxiolytics, which are used to treat depression and anxiety (chapters 4.1 and 4.3 of the British National Formulary) from primary health records. We calculated the number of participants with active medication prescriptions (i.e., a prescription dated within that period) during the baseline period (January–April 2021) and at follow-up (January–April 2022). At baseline, participants were categorized into two groups—those with active prescriptions and those without. Active medication prescriptions in the follow-up were considered as an indicator of (1) not having recovered from CMD for those with medication at baseline or (2) new case of CMD.

Covariates

We used a set of four individual covariates in this study; age, sex (female/male), ethnicity (White British/ non-White British), and number of moves during the study period. Additionally, we extracted the 2019 index of multiple deprivation (DLUHC Open Data: English Indices of Deprivation 2019—LSOA Level [opendatacommunities.org]) as a measure of small area-level socio-economic status, specifically at the lower super output area (LSOA) level.

Operationalization of moves

Participants' residential address history were accessed through the CB platform. We determined that a person moved to another address when we observed that the premove unique property reference number, a unique identifier assigned to every addressable location in the United Kingdom, was different to the postmove one. Given that some participants moved more than once during the study period, we considered the last known address as the postmove location for analyses.

Data analysis plan

We conducted the analyses using R Statistical Software (v.4.0.3; R Core Team, 2022). We calculated descriptive statistics (mean/median/n; standard deviation/[IQR]/%) for all study variables. Given the nature and objectives of the present study, we compared the pre- and postmove environmental exposure metrics to describe the changes in residential greenness and air pollution and to model their impact on participants' mental health. This type of comparison is common in the epidemiology of relocation.[29,34,35,45] Following Warkentin et al.,[34] we used a tertile approach to characterize moving patterns in the samples of participants. More specifically, we divided premove environmental exposure scores into tertiles and classified participants as moving to a "similar" area if the postmove remained in the same tertile as the premove score, to a "better quality" area if it was included in a higher tertile or to a "worse quality" area if the opposite was the case. This procedure helped us in understanding the environmental implications of the residential moves and observe how many participants moved to areas of higher, lower, or similar exposure levels.

For the modeling phase, we computed separate environmental exposure change scores by subtracting premove scores from postmove ones as done by Gao and Wang[29] and used these scores in the regression models described below. We then designed a direct acyclic graph (DAG) (Figure 1) to represent literature-based assumptions and select covariates for adjustment.[54,55] We examined the validity of the DAG for each exposure change score and study combination using the R packages *dagitty* and *lavaan*.[56,57] To do so, we checked the testable implications (i.e., pairwise marginal and conditional independencies) within our DAG following a procedure described elsewhere.[58] In line with previous authors, we considered a testable implication was unmet when its associated

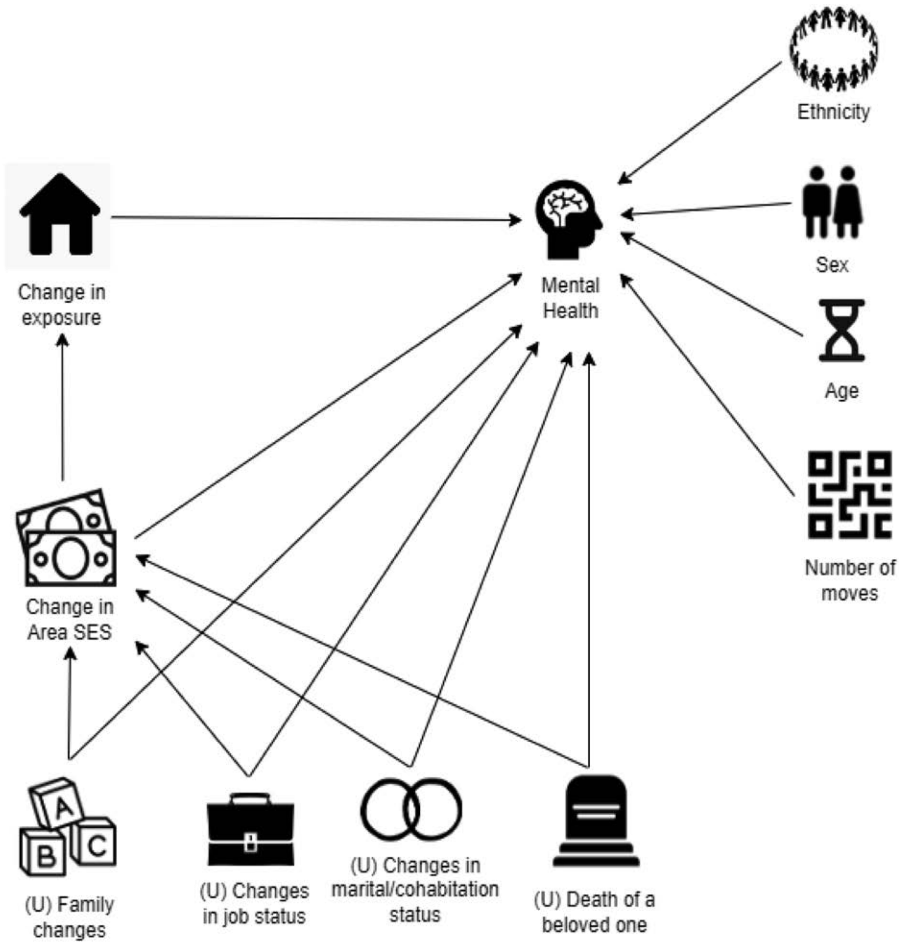

Figure 1. Directed acyclic graph regarding the expected associations between change in environmental exposures and mental health in the follow-up. The arrows indicate causal paths. All the relationships were defined based on previous literature and discussions among the authors. Variables preceded by a "(U)" are unobserved variables.

Table 1.

Description of study variables in the study samples

Sample	N	Age	Gender	Ethnicity	Medication in follow-up	Number of moves
With preexisting prescriptions	2,084	51 (20.03)	F 1,379 (66.17%) M 705 (33.83%)	WB 1,626 (78.02%) Non-WB 458 (21.98%)	No 598 (28.72%) Yes 1,486 (71.28%)	1.30 (0.67)
Without preexisting prescriptions	12,699	42.46 (17.40)	F 7,563 (59.56%) M 5,136 (40.44%)	WB 7369 (58.03%) Non-WB 5330 (41.97%)	No 10,775 (84.85%) Yes 1,924 (15.15%)	1.07 (0.29)

Scores within parentheses indicate the proportion of participants in the corresponding categories or the standard deviation in continuous variables. Ethnicity was reduced to two categories so both groups represented at least 20% of the sample and to accommodate the variable to the computational requirements of *dagitty* (i.e., testable implication checks).
F indicates female, M, Male; WB, White British.

correlation index was $r > 0.20$ and its P-value <0.05. Once the DAG was validated, we extracted the minimum set of adjustment variables with the function *adjustmentSets()* within *dagitty* R package.[7,59] We fitted logistic regression models to see whether changes in exposures predicted the presence of active medication prescriptions in the follow-up. Odds ratios in said models reflect changes in the likelihood of having prescriptions by exposure change score increases of 1 IQR.

Results

Study samples

The samples of participants (see Table 1) with and without prescriptions at baseline comprised 2084 and 12,699 people, respectively. Most participants, regardless of the sample they belonged to, were female and White British. Participants with prescriptions at baseline were almost 10 years older on average. A total of 71% of participants with prescriptions at the baseline, and 15% of participants without, had active medication prescriptions in the follow-up. Summary descriptives of the environmental exposures can be found in Supplementary Table 1; http://links.lww.com/EE/A355.

Description of changes in environmental exposures

The tertiles-based analyses (see Table 2 and Supplementary Table 2; http://links.lww.com/EE/A355) showed that most participants moved to residential settings similar to their original ones, a pattern consistent across the majority of the metrics

Table 2.

Characterization of changes in environmental exposures due to residential moves and comparison of moving patterns between participants with and without preexisting prescriptions

	Sample						Chi-squared test		
	With preexisting prescriptions			Without preexisting prescriptions					
Exposure	Exposure tertiles	Type of move	Distribution of participants	Exposure tertiles	Type of move	Distribution of participants	χ2	df	P
NDVI	(0.06, 0.19)	Decrease	452 (21.69%)	(0.07, 0.18)	Decrease	2,304 (18.14%)	18.59	2	<0.001
	(0.19, 0.23)	Same	1,005 (48.22%)	(0.19, 0.23)	Same	6,663 (52.47%)			
	(0.24, 0.43)	Increase	627 (30.09%)	(0.24, 0.47)	Increase	3,732 (20.39%)			
Green space distance decay	(0, 0.20)	Decrease	695 (33.35%)	(0, 0.22)	Decrease	4,216 (33.20%)	311.97	2	<0.001
	(0.21, 0.51)	Same	505 (24.04%)	(0.23, 0.56)	Same	5,221 (41.11%)			
	(0.51, 2.83)	Increase	888 (42.61%)	(0.57, 4.59)	Increase	3,272 (25.77%)			
$PM_{2.5}$	(0.11, 3.21)	Decrease	414 (19.87%)	(0.04, 3.63)	Decrease	3,420 (27.48%)	510.15	2	<0.001
	(3.22, 5.34)	Same	822 (39.44%)	(3.64, 5.78)	Same	6,909 (54.41%)			
	(5.35, 9.89)	Increase	848 (40.69%)	(5.79, 9.89)	Increase	2,370 (18.66%)			
PM_{10}	(0.16, 5.17)	Decrease	412 (19.77%)	(0.06, 5.9)	Decrease	3,435 (27.05%)	626.46	2	<0.001
	(5.18, 8.33)	Same	819 (39.3%)	(6, 9.15)	Same	7,095 (55.87%)			
	(8.34, 16.20)	Increase	853 (40.93%)	(9.16, 16.20)	Increase	2,169 (17.08%)			
NOx	(0.57, 9.89)	Decrease	388 (18.62%)	(0.36, 11.5)	Decrease	3,632 (28.60%)	500.90	2	<0.001
	(9.90, 17.6)	Same	821 (39.4%)	(11.6, 20.2)	Same	6,547 (51.56%)			
	(17.7, 129)	Increase	875 (41.99%)	(20.3, 189)	Increase	2,520 (19.84%)			

Numbers and numbers between parenthesis in the "distribution of participants columns" correspond to the number of participants in each group and its corresponding percentage, respectively. Increases in NDVI and distance decay to green spaces should be interpreted as environmental quality improvements, whereas increases in air pollutants as the opposite. Types of moves were defined by comparing the exposure levels of the pre- and postmove residential locations. A move was considered as a "decrease" when the participant moved to a location, which exposure levels belonged to a lower tertile (e.g., moved from second to first NDVI tertiles). The "similar" label was used for moves within the same tertile of exposure and an "increase" happened when participants moved to a location with exposure levels corresponding to a higher tertile (e.g., moving from second to third $PM_{2.5}$ tertiles).
NDVI indicates normalized difference vegetation index; NOx, nitrogen oxide; PM, particulate matter.

Table 3.

Models showing the associations between changes in environmental exposures and mental health in the follow-up

Exposure	Sample	Adjustment set	OR	z-value	P-value	95% CI
Increases in NDVI	With preexisting prescriptions	Change in IMD	0.95	–0.76	0.451	(0.84, 1.08)
	Without preexisting prescriptions	Change in IMD	0.93	–2.65	0.007	(0.88, 0.98)
Increases in proximity to green spaces	With preexisting prescriptions	Change in IMD	1.04	0.81	0.417	(0.95, 1.14)
	Without preexisting prescriptions	Change in IMD	1.05	1.97	0.049	(1, 1.10)
Increases in $PM_{2.5}$	With preexisting prescriptions	Change in IMD	1.01	0.19	0.848	(0.89, 1.15)
	Without preexisting prescriptions	Change in IMD	1.1	3.4	<0.001	(1.04, 1.16)
Increases in PM_{10}	With preexisting prescriptions	Change in IMD	1.02	0.27	0.788	(0.90, 1.15)
	Without preexisting prescriptions	Change in IMD	1.12	4.12	<0.001	(1.06, 1.19)
Increases in NOx	With preexisting prescriptions	Change in IMD	0.94	–1.71	0.087	(0.87, 1.01)
	Without preexisting prescriptions	Change in IMD	0.99	–0.85	0.395	(0.95, 1.02)

Odds ratios above one indicate higher chances of having active prescriptions in the follow-up. IQR values for the sample with preexisting prescriptions: NDVI = 0.08, distance decay to green spaces = 0.52, $PM_{2.5}$ = 2.91 (μg/m^3), PM_{10}= 4.30 (μg/m^3) and NOx (μg/m^3) = 11.56. IQR values for the sample without preexisting prescriptions: NDVI = 0.07, distance decay to green spaces = 0.50, $PM_{2.5}$ = 2.30 (μg/m^3), PM_{10}= 3.43 (μg/m^3) and NOx = 10.50 (μg/m^3). Bold numbers indicate statistically significant values.
IMD indicates Index of Multiple Deprivation; NDVI, normalized difference vegetation index; NOx, nitrogen oxide; PM, particulate matter.

considered. When looking at the moving patterns between participants with and without preexisting prescriptions, we observed that participants with preexisting prescriptions were more likely to move to areas with lower NDVI levels, greater availability to green spaces and higher concentrations of $PM_{2.5}$, PM_{10}, and NO_2. They were also less likely to move to areas of similar exposure levels than their counterparts without preexisting prescriptions. On the contrary, participants without preexisting prescriptions were more likely to move to areas with greater availability of green spaces and lower concentrations of air pollutants. They were also more likely to stay in areas of similar exposure levels.

DAG validation and modeling

The 14 testable implications comprised in the study DAG were met (r < 0.20 and P > 0.05) for every metric and sample, which meant that amendments to the DAG were not required. Results of these checks can be found in Appendix I; https://links.lww.com/EE/A352. This meant that to estimate the effect of changes in exposures on mental health in the follow-up, we needed to control for area SES.

Table 3 shows the results of the fitted regression models (see Supplementary Table 1; https://links.lww.com/EE/A352 for pre–post move change scores summary statistics and IQR). Changes in exposures did not have any impact on medication prescriptions in the sample with prescriptions at baseline. For those without prescriptions at baseline, we observed a protective effect of residential greenness. Those moving to areas with higher NDVI scores were 7% less likely to be on medication in the follow-up. However, we found a counterintuitive association between green space distance decay and prescriptions; those participants moving to areas with higher availability of green spaces were 4% more likely to be on active prescriptions in the follow-up. Regarding air pollution, moving to areas with higher $PM_{2.5}$ and PM_{10} increased the likelihood of prescriptions at follow-up by 11% and 12%, respectively. Finally, we did not observe any association with changes in NO_x levels.

Discussion

This study investigated the intersections between residential mobility, environmental exposures, and mental health in the city of Bradford. More specifically, we wanted to describe residential mobility patterns in patients with and without prescriptions for anxiolytics and antidepressants and see whether the subsequent changes in environmental exposures were related to the onset and evolution of said conditions. Using tertiles to describe changes in exposure metrics due to residential changes, we saw that most participants moved to areas with similar levels of greenness and pollution.[34] Nevertheless, our results reveal two different residential moving patterns between participants with and without prescriptions at baseline. Those with preexisting prescriptions tended to move more often during the study period and were more likely to move to less green and more polluted areas. In contrast, those movers without preexisting prescriptions were more likely to move to less polluted areas. The only exception to this trend is the availability of green spaces. Our study found that movers with preexisting prescriptions were more likely to have moved to areas with greater green space availability.

Following previous research, we also wanted to see whether the changes in environmental exposures that participants experienced due to the residential relocations affected their mental health status. This question had different implications for each of the study samples. For those with preexisting conditions, changes in environmental exposures could foster or hinder recovery, for those without preexisting conditions, environmental quality alterations could be associated with the onset of postmove disorders. We saw that changes in environmental exposures were not related to prescription status in the follow-up for those participants with prescriptions at baseline. This means that varying environmental conditions did not affect the evolution of those conditions. However, we found that environmental improvements protected against the onset of prescriptions for those without preexisting ones. More specifically, we saw that those moving to greener areas (i.e., areas with higher NDVI scores) were less likely to have active antidepressants or anxiolytics prescriptions in the follow-up and that those moving to areas with higher concentrations of $PM_{2.5}$ and PM_{10} were more likely to have active prescriptions.

We found that higher availability of green spaces led to increased odds of CMD medication in the follow-up in the sample of participants without prescriptions at baseline. Despite being theoretically counterintuitive, previous research conducted in Bradford has shown that green spaces are more prevalent in the most socio-economically vulnerable areas of the city.[7] The study also showed that people living close to unsatisfactory parks reported higher anxiety symptoms, which was interpreted by the authors as a potential indicator of safety issues and low green space quality. In a previous study conducted in Bradford, safety aspects of green spaces, such as antisocial or inappropriate behavior by other users and fears related to become a victim of verbal harassment or sexual assault, were relevant barriers for greenspace use.[60] Although it remains unknown whether this generalizable to other settings or a particularity of the city of Bradford, but it highlights the need for green space quality and design features to be taken into account.[61]

Our study clearly shows that people experiencing mental health problems tend to move more often and to worse environmental quality areas, which, in turn, may impact their ability to recover from said conditions. Overall, these differing moving patterns may reflect an environmental injustice[15] that warrants attention and action. As environmental burdens are typically concentrated in deprived urban areas, initiatives at a city level should allocate resources for improvements in these areas, to reduce this spatial inequality. Urban interventions such as low-traffic neighborhoods, low-emission zones, enhanced provision of green spaces and infrastructures, or active transport schemes could all help improving overall population mental health and reduce environmental and health inequalities.[62]

Strengths and limitations

Our study has a number of strengths. By employing a natural experimental design, we contribute to the causal understanding of how environmental determinants affect mental health, addressing a significant gap in the currently limited evidence base. We include a large population-based sample of residents in a large multiethnic city with high levels of deprivation. Using routine data, we were able to include the whole population, overcoming some of the limitations of other epidemiological studies (e.g., selection bias). Also, we used a diverse set of environmental exposures comprising residential greenness and air pollution metrics and were able to assess their impact on not only the recovery of those participants already prescribed with anxiolytics or antidepressants but also on the development of new mental health problems in previously unaffected people. The precision of measurement of geographical change in house moves, that is, using the precise geolocation of all participants at each moment of time, is another innovation worth highlighting as it contributes to the reliability of the results. In the methodological sphere, we conducted statistical analyses following current robust approaches to causal inference by not only designing a DAG but also validating it, which is still a pending issue in epidemiological research.[58,63]

Despite its interest, this study has some limitations. First, by limiting our sample to only individuals that moved during the study period, compared with the wider population, our sample over-represented females, and those of White British origin, which may compromise our ability to generalize. Second, we were unable to ascertain the reasons behind residential moves in our participants. This limitation is pervasive in studies using only routine collected health records.[25,36] These motivations might confound the environmental exposures—mental health relationships and, as shown in our DAG, we could control for their impact on exposures by adjusting for changes in area SES. However, any impact of those motivations on the environmental characteristics of the postmove residential setting happening through pathways other than that could have confounded our estimates. The use of routine data comes with further limitations that have been described elsewhere.[64,65] These are the limited number of potential confounders available in health records and the quality and completeness of data. Finally, we operationalized the presence of CMD in our participants by extracting medication prescriptions, which is neither the golden standard for mental health assessment nor comes from a systematic or formal evaluation of the mental health status of participants.

Final remarks

Our study demonstrates the importance of the neighborhoods in which we live as determinants of our mental health. We found clear examples of environmental injustice, where residents with preexisting vulnerabilities were more likely to move to areas with greater environmental burdens. We also found that neighborhood urban exposures such as residential greenness and air pollution have an impact on the onset of poor mental health problems. By targeting investment in areas of deprivation with multiple environmental burdens, we will be able to tackle these injustices and protect populations' mental health.

Conflicts of interest statement

The authors declare that they have no conflicts of interest with regard to the content of this report.

References

1. World Health Organization. World Mental Health Report. *Transforming Mental Health for All*. 2022. doi:10.1136/bmj.o1593.
2. Chlapecka A, Kagstrom A, Cermakova P. Educational attainment inequalities in depressive symptoms in more than 100,000 individuals in Europe. *Eur Psychiatry*. 2020;63:e97.
3. Henking C. Inequalities in common mental health disorders: understanding the predictors of lifetime prevalence, treatment utilisation, and helpfulness across 113 countries. *Lancet*. 2022;400(Special Issue 1):S45.
4. Prady SL, Endacott C, Dickerson J, Bywater TJ, Blower SL. Inequalities in the identification and management of common mental disorders in the perinatal period: an equity focused reanalysis of a systematic review. *PLoS One*. 2021;16:e0248631–e0248621.
5. Generaal E, Hoogendijk EO, Stam M, et al. Neighbourhood characteristics and prevalence and severity of depression: pooled analysis of eight Dutch cohort studies. *Br J Psychiatry*. 2019;215:468–475.
6. Gascon M, Sánchez-Benavides G, Dadvand P, et al. Long-term exposure to residential green and blue spaces and anxiety and depression in adults: a cross-sectional study. *Environ Res*. 2018;162:231–239.
7. Subiza-Pérez M, Krenz K, Watmuff A, et al. Social inequalities, residential greenness and common mental disorders in women: evidence from the Born in Bradford family cohort study. *Urban For Urban Green*. 2024;94:128241.
8. Turunen AW, Halonen J, Korpela K, et al. Cross-sectional associations of different types of nature exposure with psychotropic, antihypertensive and asthma medication. *Occup Environ Med*. 2023;80:111–118.
9. Klompmaker JO, Hoek G, Bloemsma LD, et al. Associations of combined exposures to surrounding green, air pollution and traffic noise on mental health. *Environ Int*. 2019;129:525–537.
10. Shin J, Park JY, Choi J. Long-term exposure to ambient air pollutants and mental health status: a nationwide population-based cross-sectional study. *PLoS One*. 2018;13:e0195607.
11. Zhang R, Zhang CQ, Rhodes RE. The pathways linking objectively-measured greenspace exposure and mental health: a systematic review of observational studies. *Environ Res*. 2021;198:111233.
12. Zundel CG, Ryan P, Brokamp C, et al. Air pollution, depressive and anxiety disorders, and brain effects: a systematic review. *Neurotoxicology*. 2022;93:272–300.
13. Borroni E, Pesatori AC, Bollati V, Buoli M, Carugno M. Air pollution exposure and depression: a comprehensive updated systematic review and meta-analysis. *Environ Pollut*. 2022;292:118245.
14. Braithwaite I, Zhang S, Kirkbride JB, Osborn DPJ, Hayes JF. Air pollution (particulate matter) exposure and associations with depression, anxiety, bipolar, psychosis and suicide risk: a systematic review and meta-analysis. *Environ Health Perspect*. 2019;127:126002.
15. Murray MH, Buckley J, Byers KA, et al. One health for all: advancing human and ecosystem health in cities by integrating an environmental justice lens. *Annu Rev Ecol Evol Syst*. 2022;53:403–426.
16. Mitchell RJ, Richardson EA, Shortt NK, Pearce JR. Neighborhood environments and socioeconomic inequalities in mental well-being. *Am J Prev Med*. 2015;49:80–84.
17. Llop S, Ballester F, Estarlich M, et al. Social factors associated with nitrogen dioxide (NO2) exposure during pregnancy: the INMA-Valencia project in Spain. *Soc Sci Med (1982)*. 2011;72:890–898.
18. Venter ZS, Figari H, Krange O, Gundersen V. Environmental justice in a very green city: spatial inequality in exposure to urban nature, air pollution and heat in Oslo, Norway. *Sci Total Environ*. 2023;858:160193.
19. Verbeek T. Unequal residential exposure to air pollution and noise: a geospatial environmental justice analysis for Ghent, Belgium. *SSM Popul Health*. 2019;7:100340.
20. Klompmaker JO, Hart JE, Bailey CR, et al. Racial, ethnic, and socioeconomic disparities in multiple measures of blue and green spaces in the United States. *Environ Health Perspect*. 2023;131:1–9.
21. Aamodt G, Nordh H, Nordbø ECA. Relationships between socio-demographic/ socio-economic characteristics and neighborhood green space in four Nordic municipalities—results from NORDGREEN. *Urban For Urban Gree*. 2023;82:127894.
22. Astell-Burt T, Mitchell R, Hartig T. The association between green space and mental health varies across the lifecourse. a longitudinal study. *J Epidemiol Community Health*. 2014;68:578–583.
23. Pizzi C, Moirano G, Moccia C, et al. Socioeconomic position during pregnancy and pre-school exposome in children from eight European birth cohort studies. *Soc Sci Med (1982)*. 2024;359:117275.
24. Robinson O, Tamayo I, de Castro M, et al. The urban exposome during pregnancy and its socioeconomic determinants. *Environ Health Perspect*. 2018;126:077005.
25. Drewnowski A, Arterburn D, Zane J, et al. The Moving to Health (M2H) approach to natural experiment research: a paradigm shift for studies on built environment and health. *SSM Popul Health*. 2019;7:100345.
26. Gillespie BJ, Fokkema T. Life events, social conditions and residential mobility among older adults. *Popul Space Place*. 2024;30:e2706.
27. Saucy A, Gehring U, Olmos S, et al. Effect of residential relocation on environmental exposures in European cohorts: an exposome-wide approach. *Environ Int*. 2023;173:107849.
28. Heo S, Afanasyeva Y, Trasande L, Bell ML, Ghassabian A. Residential mobility in pregnancy and potential exposure misclassification of air pollution, temperature, and greenness. *Environ Epidemiol*. 2023;7:e273.
29. Gao S, Wang Y. Aging in climate change: unpacking residential mobility and changes of social determinants of health in southern United States. *Health Place*. 2024;88:103268.
30. Antonakos CL, Coulton CJ, Kaestner R, Lauria M, Porter DE, Colabianchi N. Built environment exposures of adults in the moving to opportunity experiment. *Housing Stud*. 2020;35:703–719.
31. Craig P, Katikireddi SV, Leyland A, Popham F. Natural experiments: an overview of methods, approaches, and contributions to public health intervention research. *Annu Rev Public Health*. 2017;38:39–56.
32. Craig P, Cooper C, Gunnell D, et al. Using natural experiments to evaluate population health interventions: new Medical Research Council guidance. *J Epidemiol Community Health*. 2012;66:1182–1186.
33. Crane M, Bohn-Goldbaum E, Grunseit A, Bauman A. Using natural experiments to improve public health evidence: a review of context and utility for obesity prevention. *Health Res Policy Syst*. 2020;18:48.
34. Warkentin S, De Bont J, Abellan A, et al. Changes in air pollution exposure after residential relocation and body mass index in children and adolescents: a natural experiment study. *Environ Pollut*. 2023;334:122217.
35. Rachele JN, Mavoa S, Sugiyama T, et al. Changes in neighbourhood walkability and body mass index: an analysis of residential mobility from a longitudinal multilevel study in Brisbane, Australia. *Health Place*. 2024;87:103245.
36. Pedde M, Adar SD. Invited perspective: changing places—how moving histories can help map the health impacts of people's environmental exposures. *Environ Health Perspect*. 2024;132:91303.
37. Graif C, Arcaya MC, Diez Roux AV. Moving to opportunity and mental health: exploring the spatial context of neighborhood effects. *Soc Sci Med (1982)*. 2016;162:50–58.
38. Lucas JA, Hsu A, Heintzman J, et al. The Association of Mobility, Social Deprivation, and Pediatric Primary Care Outcomes in Community Health Centers. *J Pediatr*. 2023;259:113465.
39. Yen IH, Bennett A, Allen S, et al. Childhood residential mobility and mental and physical health in later life: findings from the reasons for geographic and racial differences in stroke (REGARDS) study. *J Appl Gerontol*. 2023;42:1859–1866.
40. Edwards L, Wilkinson P, Rutter G, Milojevic A. Health effects in people relocating between environments of differing ambient air pollution concentrations: a literature review. *Environ Pollut*. 2022;292:118314.
41. Alcock I, White MP, Wheeler BW, Fleming LE, Depledge MH. Longitudinal effects on mental health of moving to greener and less green urban areas. *Environ Sci Technol*. 2014;48:1247–1255.
42. Mark Noordzij J, Beenackers MA, Oude Groeniger J, Van Lenthe FJ. Effect of changes in green spaces on mental health in older adults: a fixed effects analysis. *J Epidemiol Community Health*. 2020;74:48–56.
43. Tunstall H, Mitchell R, Pearce J, Shortt N. The general and mental health of movers to more- and less-disadvantaged socio-economic and physical environments within the UK. *Soc Sci Med*. 2014;118:97–107.
44. Tunstall H, Pearce JR, Shortt NK, Mitchell RJ. Residential mobility and the association between physical environment disadvantage and general and mental health. *J Public Health (Oxf)*. 2015;37:563–572.
45. Chen G, Qian ZM, Zhang J, et al. Associations between changes in exposure to air pollutants due to relocation and the incidence of 14 major disease categories and all-cause mortality: a natural experiment study. *Environ Health Perspect*. 2024;132:097012.
46. Mueller N, Rojas-Rueda D, Khreis H, et al. Socioeconomic inequalities in urban and transport planning related exposures and mortality: a health impact assessment study for Bradford, UK. *Environ Int*. 2018;121:931–941.
47. Sohal K, Mason D, Birkinshaw J, et al. Connected Bradford: a whole system data linkage accelerator. *Wellcome Open Res*. 2022;7:26.

48. Krenz K, Dhanani A, McEachan RRC, Sohal K, Wright J, Vaughan L. Linking the urban environment and health: an innovative methodology for measuring individual-level environmental exposures. *Int J Environ Res Public Health*. 2023;20:1953.
49. U.S. Geological Survey. Landsat 8-9 OLI level-2 science products digital object identifier. Published online 2022. https://doi.org/10.5066/P9OGBGM6. Accessed 5 December 2022.
50. Ordnance Survey. OS address base premium. 2022. www.ordnancesurvey.co.uk/products/addressbase-premium. Accessed 5 December 2022.
51. Ordnance Survey. OS MasterMap Highways Network and OS MasterMap Highways Network—Paths [GeoPackage geospatial data]. 2022. https://digimap.edina.ac.uk. Accessed 5 December 2022.
52. Ordnance Survey. OS open greenspace. 2022. https://www.ordnancesurvey.co.uk/products/os-open-greenspace. Accessed 5 December 2022.
53. Konstantinoudis G, Padellini T, Bennett J, Davies B, Ezzati M, Blangiardo M. Long-term exposure to air-pollution and COVID-19 mortality in England: a hierarchical spatial analysis. *Environ Int*. 2021;146:106316.
54. Elwert F. Graphical causal models. In: Morgan S, ed. *Handbook of Causal Analysis for Social Research*. 2013:245-273. doi:10.1007/978-1-4471-6699-3_13.
55. Pearl J. *Causality*. Cambridge University Press; 2009. doi: 10.1017/CBO9780511803161.
56. Rosseel Y. lavaan: an R package for structural equation modeling. *J Stat Soft*. 2012;48:1–36.
57. Textor J, van der Zander B, Gilthorpe MS, Liśkiewicz M, Ellison GT. Robust causal inference using directed acyclic graphs: the R package "dagitty.". *Int J Epidemiol*. 2017;45:dyw341–dy1894.
58. Ankan A, Wortel IMN, Textor J. Testing graphical causal models using the R Package "dagitty." *Curr Protoc*. 2021;1:1–22.
59. Subiza-Pérez M, García-Baquero G, Fernández-Somoano A, et al. Social inequalities, green and blue spaces and mental health in 6–12 years old children participating in the INMA cohort. *Health Place*. 2023;83:103104.
60. Cronin-de-Chavez A, Islam S, McEachan RRC. Not a level playing field: a qualitative study exploring structural, community and individual determinants of greenspace use amongst low-income multi-ethnic families. *Health Place*. 2019;56:118–126.
61. Knobel P, Dadvand P, Maneja-Zaragoza R. A systematic review of multi-dimensional quality assessment tools for urban green spaces. *Health Place*. 2019;59:102198.
62. Nieuwenhuijsen M, De Nazelle A, Garcia-Aymerich J, Khreis H, Hoffmann B. Shaping urban environments to improve respiratory health: recommendations for research, planning, and policy. *Lancet Respir Med*. 2024;12:247–254.
63. Tennant PWG, Murray EJ, Arnold KF, et al. Use of directed acyclic graphs (DAGs) to identify confounders in applied health research: review and recommendations. *Int J Epidemiol*. 2021;50:620–632.
64. Grzeskowiak LE, Gilbert AL, Morrison JL. Methodological challenges in using routinely collected health data to investigate long-term effects of medication use during pregnancy. *Ther Adv Drug Saf*. 2013;4:27–37.
65. Mc Cord KA, Hemkens LG. Using electronic health records for clinical trials: where do we stand and where can we go? *CMAJ*. 2019;191:E128–E133.