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Longitudinal mental health associations of relocation to supportive versus adverse neighborhood environments in the Netherlands

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ABSTRACT

Background: Mental health status may be associated with residential neighborhoods' physical and social characteristics; however, longitudinal evidence is limited, and the findings are inconsistent.
Objectives: To examine the longitudinal associations between neighborhood physical and social environments and mental health among adults after residential relocation.
Methods: We used national-representative panel data of 3000 adults between 2008 and 2013 in the Netherlands. We included movers relocating to neighborhood environments identified as health-supportive or adverse; non-movers served as the control group. Mental health was measured pre- and post-move using the Mental Health Inventory. Time-varying exposure to physical environmental factors (i.e., green space, blue space, air pollution, and population density) and social environmental factors (i.e., socioeconomic deprivation and social fragmentation) were assigned based on adults' residential neighborhood histories. We used propensity score matching to select non-movers from the control group and difference-in-difference regressions to estimate the associations between environmental changes and mental health.
Results: Our results showed that decreases in fine particulate matter ($\beta = -3.869$, 95% CI: [-7.583, -0.155]), population density ($\beta = -5.893$, 95% CI: [-9.468, -2.319]), and socioeconomic deprivation ($\beta = -4.756$, 95% CI: [-7.800, -1.712]) were significantly associated with improvements in mental health. An increase in neighborhood social fragmentation was significantly associated with improvements in mental health ($\beta = -3.520$, 95% CI: [-6.742, -0.298]). We observed null associations between changes in mental health due to changes in green and blue space.
Conclusions: Following relocation, changed neighborhood environmental conditions appear to have longitudinal mental health associations. Moving to a neighborhood with less air pollution, lower population density, and reduced socioeconomic deprivation was mental health-supportively associated. However, the finding that greater social fragmentation contributes to mental health improvements requires further investigation.

1. Introduction

Mental illness is the leading cause of disability in high-income countries (GBD 2019 Mental Disorders Collaborators, 2022), highlighting mental health as a critical public health concern (Patel et al., 2018). Increasing longitudinal and meta-analytical epidemiological evidence suggests that residential neighborhood physical environments such as green space, blue space, air pollution, population density (Cao et al., 2023; Dzhambov, 2018; Geary et al., 2023; Gonzales-Inca et al., 2022; Mouly et al., 2023; Nobile et al., 2023; Sui et al., 2023; Sundquist et al., 2004; Tarkiainen et al., 2021; Zare Sakhvidi et al., 2022) and social settings including socioeconomic deprivation, social fragmentation (Richardson et al., 2015; Sui et al., 2022) are associated with mental health.

To disintermediate these neighborhood environment-health associations, study designs focused on residential relocation have gained some popularity, although their application in mental health research remains limited (Alcock et al., 2015, 2014; Boje-Kovacs et al., 2023; Graif et al., 2016; Mouly et al., 2023; Nguyen et al., 2023; van den Bosch et al., 2015; Weimann et al., 2015; White et al., 2017). Two advantages of such relocation studies are noteworthy versus longitudinal studies that do not incorporate residential histories (Baranyi et al., 2019; Liu et al., 2021; Pun et al., 2019; Tarkiainen et al., 2021): First, relocation typically leads to substantial changes in neighborhood environments, providing more

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robust assessments of environment-mental health associations than studies based on non-movers for whom environmental changes are frequently incremental (Braun et al., 2016; Kivimäki et al., 2021). Second, residential relocation study designs mitigate the potential risk of reverse causation, following a temporal sequence of environmental changes and subsequent mental health outcomes (Saucy et al., 2024).

However, only a few longitudinal studies have examined changes in movers' mental health after relocation to a different neighborhood. These studies tentatively suggested, for example, that moving to less socio-economically deprived (Boje-Kovacs et al., 2023; Graif et al., 2016; Nguyen et al., 2023; White et al., 2017) and greener neighborhoods (Alcock et al., 2014, 2015) was associated with improved mental health. By contrast, others (Mouly et al., 2023; van den Bosch et al., 2015; Weimann et al., 2015) found null associations between changes in neighborhood green spaces and changes in mental health.

Some limitations must be acknowledged, although these studies provide vital insights. First, these studies typically assessed a single exposure in isolation and disregarded co-occurring changes in other environmental exposures (Alcock et al., 2014; Boje-Kovacs et al., 2023; Graif et al., 2016; Nguyen et al., 2023; van den Bosch et al., 2015; Weimann et al., 2015; White et al., 2017). Thus, the estimated association between a specific environmental exposure and changes in mental health may be biased without controlling for other environmental factors. Second, previous studies (Alcock et al., 2015, 2014; Mouly et al., 2023; Nguyen et al., 2023; van den Bosch et al., 2015) overlooked that mental health before a move is related to post-move mental health and likely affects people's neighborhood preference (i.e., residential self-selection bias). For example, people with mental health illnesses are more likely to move to socio-economically deprived neighborhoods (Tunstall et al., 2014). We note that in order to obtain more unbiased estimates of the associations between changes in mental health and changes in the environment, it is crucial to control for baseline mental health status.

To address these research gaps, we examined the longitudinal associations between neighborhood physical and social environmental characteristics and mental health in a representative sample of Dutch adults. We used econometric approaches including a difference-in-difference model combined with propensity score matching to test two hypotheses: 1) moving into health-supportive neighborhood physical and social environments (i.e., those possessing more green or blue space, lower levels of air pollution, population density, socioeconomic deprivation, or lower social fragmentation) is associated with improvements in people's mental health; and 2) moving into neighborhoods with adverse physical and social environments (i.e., less green or blue space, higher air pollution, population density, socioeconomic deprivation, or higher social fragmentation) is associated with adverse consequences to people's mental health.

2. Material and methods

2.1. Study sample

We based this study on the Longitudinal Internet Studies for the Social Sciences (LISS) panel, an ongoing and representative survey of Dutch households collected by Centerdata (Scherpenzeel and Das, 2010). The survey selected households based on their residential address and originated from a probability sample drawn from the population register of Statistics Netherlands. Survey participants were household members aged 16 years and older who lived at their home address more than four days per week. The panel members completed a baseline health survey in November 2007, containing 4200 households with approximately 6700 individuals. We included only adults aged ≥18 in our study sample. Respondents completed health surveys each November between 2008 and 2013. An in-depth description of the recruitment strategy is available elsewhere (Scherpenzeel, 2009).

We defined respondents who moved between November 1st of the previous wave and November 1st of the current wave as movers (Fig. 1). We applied the following exclusion criteria to movers who 1) moved more than once in a given year; 2) moved or did not complete the survey in the year before moving or the year after moving; 3) had incomplete individual-level or neighborhood-level characteristics during the study period. Exclusion criteria for the non-movers were 1) moving during the study period and 2) having incomplete individual-level or neighborhood-level characteristics during the study period. Fig. 2 summarizes the sample selection. This four-wave sample included 3233 adults in 2009 ($N_{movers} = 75$, $N_{non\text{-}movers} = 3158$), 3436 adults in 2010 ($N_{movers} = 77$, $N_{non\text{-}movers} = 3359$), 3389 adults in 2011 ($N_{movers} = 73$, $N_{non\text{-}movers} = 3316$), and 3192 adults in 2012 ($N_{movers} = 72$, $N_{non\text{-}movers} = 3120$).

2.2. Study design

Our study is based on Rubin's (1974) counterfactual framework. In this study, changes in the neighborhood environment occurred after residential relocation. Each mover i had a mental health outcome after moving into a new neighborhood environment of Y_i^1 and a potential mental health outcome if staying in the original neighborhood environment of Y_i^0. Therefore, the association between the changed neighborhood environment and mental health for each mover is Y_i^1-Y_i^0, and for each mover, the potential mental health outcome Y_i^0 can neither be observed nor measured. We chose non-movers who shared similar baseline characteristics with movers. Thus, for each mover, Y_i^0 can be represented by the subsequent mental health outcomes of non-movers.

2.3. Measures of mental health

We measured subjects' mental health using the five-item Mental Health Inventory (MHI-5) (Ware et al., 2000; Ware and Gandek, 1998), a widely used assessment tool (Churchill and Smyth, 2022; Vries et al., 2016). Respondents were posed three questions on how often they perceived mental health problems (i.e., "feeling anxious"; "feeling depressed"; "feeling down and cannot cheer up") and how often they felt well mentally (i.e., "feeling calm and peaceful"; "feeling happy") over the previous month. Response options on a six-item Likert scale ranged from "never" (1) to "continuously" (6) and were rescaled from 0 to 5. To ensure consistency with previous studies (Ringdal and Rootjes, 2022; van der Velden et al., 2019), we reverse-coded two questions on good mental health status to calculate the total MHI-5 scores before converting them to a 100-point scale. A higher score indicated more mental health problems and vice versa. The MHI-5 measure had high internal consistency (Cronbach's alpha = 0.842). For each participant, we calculated MHI-5 scores in the year before moving and the year after moving.

2.4. Measures of neighborhood environments

We annually assessed people's environmental exposures at their places of residence between 2008 and 2013 based on their four-digit postal code areas as is standard practice (Gong et al., 2016;

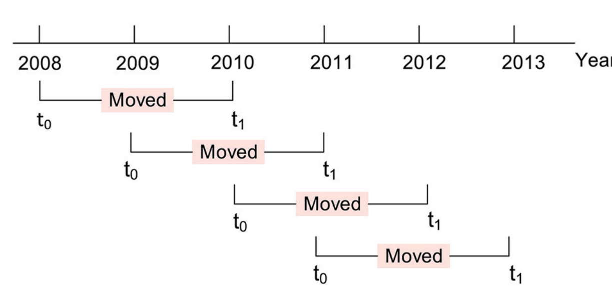

Fig. 1. Study setting.

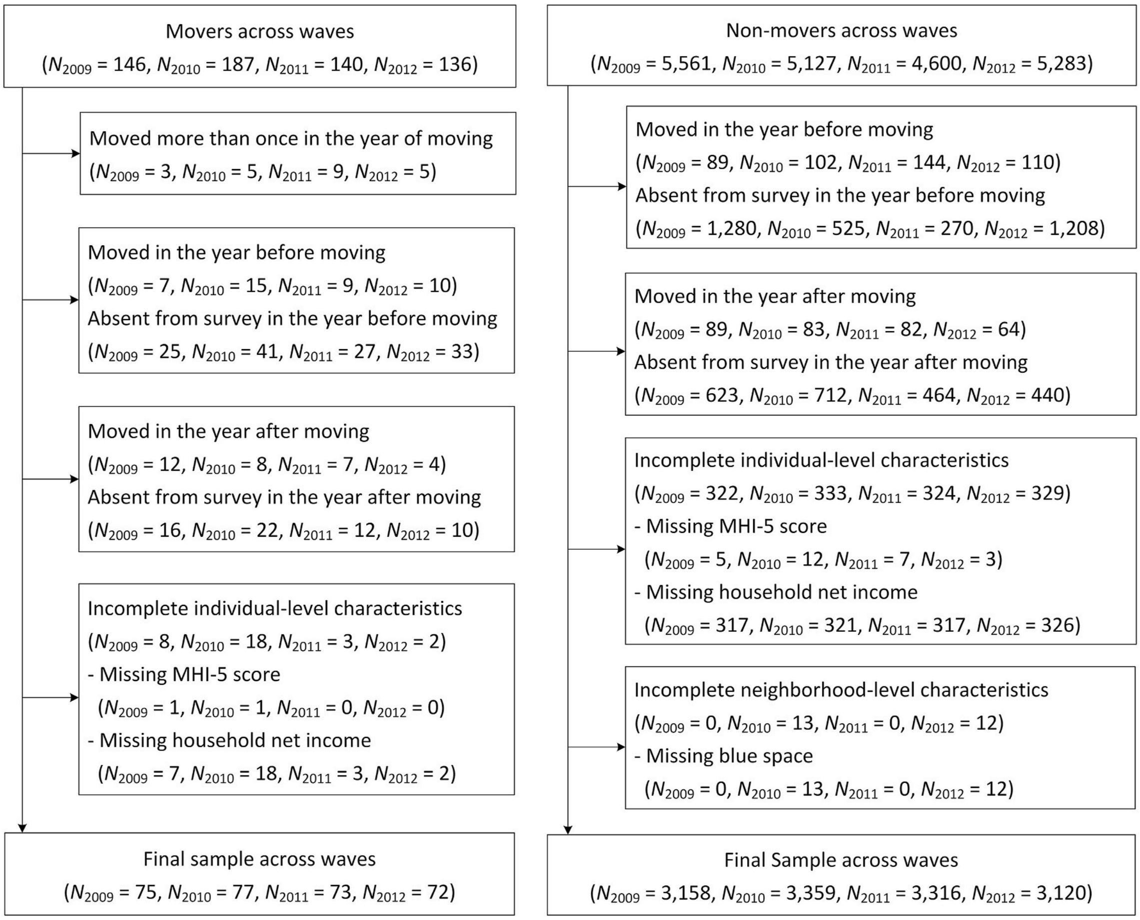

Fig. 2. Selection of the study sample based on the LISS panel.

Groenewegen et al., 2018). The area covered by four-digit postal codes varied between 0.01 km^2 and 445 km^2 with a mean of 10.2 km^2 (standard deviation [SD] = 19.7). We captured the address locations of all participants in a wave annually on November 1st. Minor random noise (<1% of the median of the exposure distribution) (see Supplementary Table S1, page 1) was added to each exposure by Centerdata to avoid re-identifying the respondents.

2.4.1. Neighborhood physical environments

Green space was measured using the normalized difference vegetation index (NDVI) (Tucker, 1979). Input data was from Landsat images accessible through the Google Earth Engine at a 30 m × 30 m spatial resolution. We incorporated cloud-free images in the Netherlands between May and September for each wave. To avoid distortions towards zero, we masked pixels with NDVI values ≤ 0 referring to, for example, water and built-up areas before averaging the pixel values for each neighborhood (Gonzales-Inca et al., 2022; Hartley et al., 2021). Higher positive NDVI values represent higher levels of vegetation.

Blue space was mapped for each wave using the normalized difference water index (NDWI) (McFeeters, 1996) with a spatial resolution of 30 m. We obtained input data for the NDWI from satellite imagery and pre-processed this data as we had the NDVI data. Due to the sparsity of pixels referring to blue spaces (i.e., NDWI >0), we further reclassified the NDWI into yearly binary maps distinguishing water- and non-waterbodies before calculating the proportion of blue space in each neighborhood (Helbich et al., 2022).

Air pollution was represented by yearly average concentrations of ambient $PM_{2.5}$ (V4.EU.03) (Hammer et al., 2020; van der Velden et al., 2019). The gridded $PM_{2.5}$ concentration data were estimated by the GEOS-Chem chemical transport model relating the aerosol optical depth from satellite retrievals to near-surface concentrations and subsequently calibrated by geographically weighted regression with ground-based observations. We then used bilinear interpolation to resample the grids from approximately 1 km × 1 km (0.01° × 0.01°) to a 30 m spatial resolution to align with the other exposures and because 8.4 percent of the postal code areas are less than 1 km^2.

Population density was calculated yearly on January 1st as the number of inhabitants within a neighborhood (i.e., 1000 inhabitants per km^2) based on data obtained from Statistics Netherlands.

2.4.2. Neighborhood social environments

Socioeconomic deprivation was scored on a composite index (Allik et al., 2020) that summed the z-scored unemployment rate, standardized median household income (reverse coded), and the fraction of households with a standardized income below the poverty line (Hagedoorn et al., 2020). We acquired input data for this index from the Dutch population register on January 1st for each wave. Higher index scores indicated higher levels of socioeconomic deprivation and vice versa.

The social fragmentation index aimed to capture community integration (Fagg et al., 2008; Li et al., 2016). This composite score is based on the summed z-scores of the proportion of adult residents ($\geq$18 years) who were unmarried, lived in a single-person household, and had moved to the address within the last 12 months (Hagedoorn and Helbich, 2021). We acquired input indicators from the Dutch population register data for each wave yearly on January 1st. Higher index scores referred to higher levels of social fragmentation and vice versa.

2.4.3. Changes in neighborhood environments due to relocation

We measured changes in neighborhood environments by subtracting the exposure values in the year before moving from that in the year of an individual's move. To mitigate the risk of possible measurement errors, we only considered residential moves with a 10% or greater change in the values of exposures. Those respondents with <10% changes were excluded ($2 \leq N \leq 82$). A health-supportive relocation occurred when there was a ≥10% increase in NDVI or blue space, a ≥10% decrease in $PM_{2.5,}$ population density, socioeconomic deprivation, or social fragmentation. A health-adverse relocation was with a ≥10% decrease in NDVI or blue space, a ≥10% increase in $PM_{2.5,}$ population density, socioeconomic deprivation, or social fragmentation. We assumed changes in non-movers' neighborhood environmental exposures within any year as minor and did not account for those. In total, we distinguished twelve types of environmental changes (see Supplementary Table S2, page 1) and examined each individually.

2.5. Covariates

We extracted individual-level data from the survey for the years before and after relocation. The covariate selection was guided by previous studies (Banay et al., 2019; Mouly et al., 2023; Nobile et al., 2023). Factors we included were gender (female, male), age (in years), marital status (married, not married, never married), household type (couple with children, couple without children, single with children, single, other), employment status (employed, unemployed), highest education level (low, medium, high), and monthly household net income level (low ≤2000 euros, medium = 2000–4000 euros, high ≥4000 euros).

We identified relocation-related life events between the year of a move and the year prior, as such events can significantly impact residential relocation decisions (Geist and McManus, 2008) and possibly mental health (Rahe, 1979). These events included change in marital status (no change, entering into marriage, end marriage due to divorce or widow), change in number of household members (no change, increase, decrease), change in employment status (no change, get employed, job loss), change in household net income level (no change, increase, decrease), and change in highest education level (no change, go to college, drop out of college).

2.6. Statistical analyses

2.6.1. Propensity score matching

Propensity score matching is a statistical approach for constructing control groups comparable to the study group (Rosenbaum and Rubin, 1983; Rubin, 1973). A propensity score refers to the conditional probability of residential relocation based on a set of observed covariates (Rosenbaum and Rubin, 1983). Confounders (i.e., variables affecting the probability of residential relocation and mental health) and predictors of mental health (i.e., variables unrelated to residential relocation but affecting mental health) should be included as covariates in the propensity score model (Brookhart et al., 2006; Cuong, 2013). Matching each mover with one or several non-movers by a single score rather than multiple variables is advantageous to achieve covariate similarity between the study and control group (Rosenbaum and Rubin, 1983).

We obtained propensity scores using logistic regression (Rosenbaum, 2007) and considered covariates referring to previous studies (Coulter and Scott, 2015; Lee et al., 1994; Lund et al., 2018; Lundholm et al., 2004). These covariates included demographics and socioeconomic characteristics (i.e., gender, age, marital status, household type, employment status, highest education level, household net income level, MHI-5 score) and neighborhood characteristics (i.e., NDVI, blue space, $PM_{2.5}$, population density, socioeconomic deprivation, social fragmentation) in the year before moving. Furthermore, we considered moving-related life events (i.e., change in marital status, change in the number of household members, change in employment status, change in household net income level, change in highest education level) between the year before moving and the year of a move.

We separately matched movers in different waves with non-movers. The matching procedure was performed for the relocation periods 2009, 2010, 2011, and 2012 and included twelve parameters that could identify variances between the origination and destination neighborhoods (see Section 2.4.3), leading to forty-eight matched datasets. After ensuring an adequate common area for the propensity score between non-movers and movers through boxplots, we used a greedy matching algorithm (i.e., nearest neighbor matching within a caliper of 0.25 standard deviations) to identify the best available match among the controls (Austin, 2011; Rosenbaum and Rubin, 1985). As recommended in previous scholarship (Abadie et al., 2004; Abadie and Imbens, 2011), the ratio was set to 1:4 to achieve a covariate balance between the study and the control group. We assessed the covariate balance across both groups through standardized mean differences. We regarded a standardized mean difference of <0.25 as a well-balanced match (Stuart, 2010; Stuart and Rubin, 2007).

To obtain an adequate sample size, we pooled movers and matched non-movers who experienced the same changes in environmental exposures but at different relocation times as our study and control groups. This approach was consistent with previous studies (Aranda, 2015). We then recalculated the standardized mean differences between the pooled study and control group to assess the covariates' balance. We used the 'MatchIt' package (Ho et al., 2011) in the R software, version 4.3.1 (R Core Team, 2023).

2.6.2. Difference-in-difference regression

We estimated the environmental-health associations by a difference-in-difference model. The model is as follows:

$$y_{it} = \delta D_i T_t + u_i + \lambda_t + \eta x_{it} + \varepsilon_{it} \quad (1)$$

where y_{it} indicates the MHI-5 score for respondent i in year t; $D_i T_t$ refers to the interaction term between the dummy variable D_i indicating the participant group (1 = movers who relocated into a more health-supportive or health-adverse environment; 0 = non-mover) and the dummy variable T_t indicating the period (1 = the year after moving; 0 = the year before moving); δ is the difference-in-difference estimate capturing the association between health-supportive or adverse relocation and movers' MHI-5 scores; u_i represents individual fixed effects; λ_t controls for specific year fixed effects; x_{it} indicates a set of time-varying covariates possibly associated with changes in mental health; ε_{it} is the error term. In this model, u_i and λ_t are used to mitigate confounding effects of unobserved and unmeasured time-invariant group differences (Donald and Lang, 2007).

Guided by previous studies (Cleary et al., 2019; Noordzij et al., 2020), we included time-varying covariates at the individual level (i.e., age, marital status, household type, employment status, highest education level, household net income level) and neighborhood level (i.e., NDVI, blue space, $PM_{2.5}$, population density, socioeconomic deprivation, social fragmentation) to mitigate possible confounding of other environmental exposures following residential relocation.

We fitted the regression separately to obtain an estimate for each changed environmental exposure. Due to dependencies in each participant's repeatedly measured MHI-5 scores, we calculated cluster-robust standard errors at the individual level. The regressions were estimated using the plm (Croissant and Millo, 2008) and clubSandwich R packages (Pustejovsky, 2020). We adhered to the Strengthening the Reporting of Observational Studies in Epidemiology statement (von Elm et al., 2007).

3. Results

3.1. Descriptive statistics

Table 1 shows the baseline characteristics of movers. There were 297 movers across the waves, of which 52% were female. Movers had worse baseline mental health (26.47 ± 17.60 ≤ mean MHI-5 score ≤32.59 ± 15.98) compared with non-movers (24.25 ± 16.10 ≤ mean MHI-5 score ≤25.38 ± 16.38). In the year before moving, the mean age of movers

Table 1
Baseline characteristics of movers ($N = 297$).

Variables		Variables	
MHI-5 score [Mean (SD)]	29.10 (16.70)	NDVI [Mean (SD)]	0.41 (0.12)
Age (in years) [Mean (SD)]	43.39 (16.66)	Blue space [Mean (SD)]	0.04 (0.12)
Gender [N (%)]		Population density (1000 inhabitants per km^2) [Mean (SD)]	3.55 (3.70)
Male	144 (48.5)	$PM_{2.5}$ (μg/m^3) [Mean (SD)]	16.06 (2.05)
Female	153 (51.5)	Socioeconomic deprivation [Mean (SD)]	0.61 (2.41)
Marital status [N (%)]		Social fragmentation [Mean (SD)]	1.47 (2.93)
Married	135 (45.5)	Change in household members [N (%)]	
Not married	48 (16.2)	No change	241 (81.1)
Never married	114 (38.4)	Increase	14 (4.7)
Household type [N (%)]		Decrease	42 (14.1)
Single	76 (25.6)	Change in marital status [N (%)]	
Couple without child(ren)	120 (40.4)	No change	272 (91.6)
Couple with child (ren)	87 (29.3)	Enter into marriage	16 (5.4)
Single with child (ren)	10 (3.4)	End marriage	9 (3.0)
Other	4 (1.3)	Change in employment status [N (%)]	
Employment status [N (%)]		No change	269 (90.6)
Employed	180 (60.6)	Get employed	16 (5.4)
Unemployed	117 (39.4)	Job loss	12 (4.0)
Income level [N (%)]		Change in income level [N (%)]	
High	61 (20.5)	No change	233 (78.5)
Medium	138 (46.5)	Increase	21 (7.1)
Low	98 (33.0)	Decrease	43 (14.5)
Education level [N (%)]		Change in education level [N (%)]	
High	146 (49.2)	No change	291 (98.0)
Medium	103 (34.7)	Go to college	6 (2.0)
Low	48 (16.2)	Drop out of college	0 (0.0)

Note: MHI-5: five-item Mental Health Inventory; Data source: Longitudinal Internet Studies for the Social Sciences panel; Landsat images in Google Earth Engine; Satellite-derived $PM_{2.5}$ European Regional Estimates (V4.EU.03); Statistics Netherlands; Dutch population register.

was 43 years (SD ± 17). 46% of movers were married, 40% were couples without children, 61% were employed, 47% were middle-income earners, and 49% had a high education level. The Mann-Whitney U-tests and Chi-squared tests indicated that several baseline characteristics (e.g., age, education level) and life events (e.g., change in household members, change in marital status) significantly differed between movers and non-movers (see Supplementary Table S3, page 2–5), which underscored the importance of matching movers with subjects from the control group.

3.2. Propensity score matching

The boxplots in Supplementary Figs. S1 and S2 (page 6–11) indicate adequate areas in common for the propensity scores among movers and non-movers. Over 90% of the movers matched with eligible non-movers per wave as control cases. The propensity score matching provided a new set of non-movers as control groups with a sample size for movers ($93 \leq N \leq 147$) and matched non-movers ($328 \leq N \leq 489$) (see Supplementary Table S4, page 12).

Supplementary Figs. S3 and S4 (page 13–22) demonstrate remarkable changes in the covariates' balance among the two groups before and after matching. In total, we included 39 covariates in the propensity score matching. Before matching, several covariates ($1 \leq N \leq 14$) were unbalanced, with a standardized mean difference of >0.25 among movers and unmatched non-movers. After matching, most covariates ($36 \leq N \leq 39$) were well-balanced, with a standardized mean difference of <0.25 among movers and matched non-movers. We pooled the movers and the matched non-movers across four waves, then re-tested the standardized mean difference of covariates. In the case of each of the eleven neighborhood environmental factors, the standardized mean difference of all covariates remained under 0.25 (except for the age of movers to neighborhoods with more blue spaces), suggesting well-balanced covariates (see Supplementary Tables S5 and S6, page 23–26).

3.3. Difference-in-difference regression estimates

Fig. 3 summarizes the difference-in-difference estimates for the associations of moving into health-supportive or adverse neighborhoods based on the MHI-5 scores. Note that the number of movers to higher $PM_{2.5}$ neighborhoods was insufficient to conduct an analysis ($N = 22$). Supplementary Tables S7–S12 (page 27–38) report the numerical model results. The results show decreases in $PM_{2.5}$ ($\beta = -3.869$, 95% CI: [−7.583, −0.155]), population density ($\beta = -5.893$, 95% CI: [−9.468, −2.319]), and socioeconomic deprivation ($\beta = -4.756$, 95% CI: [−7.800, −1.712]) were significantly associated with decreases in MHI-5 scores (i.e., improved mental health). However, increases in neighborhood social fragmentation ($\beta = -3.520$, 95% CI: [−6.742, −0.298]) were significantly associated with decreases in MHI-5 scores (i.e., improved mental health). We did not observe significant associations between the changes in NDVI or blue space and MHI-5 score changes.

4. Discussion

4.1. Principal findings

This longitudinal study was among the few to examine the association between moving to a health-supportive or adverse neighborhood environment and movers' mental health. In partial confirmation of our first hypothesis, moving to neighborhoods with lower air pollution, lower population density, or lower socioeconomic deprivation was associated with improvements in mental health. We observed null associations for moving to other health-supportive neighborhood-based environments (i.e., more green or blue spaces or lower social fragmentation). Contrary to our second hypothesis, we found that relocating to neighborhoods characterized by increased social fragmentation was beneficially associated with mental health. Furthermore, relocating to neighborhoods with other adverse environmental exposures, including a lack of green or blue spaces, more air pollution, higher population density, and more socioeconomic deprivation, did not show any significant associations with changes in mental health.

4.2. Interpretation of the findings and available evidence

The finding that moving to less air-polluted neighborhoods was associated with better mental health agrees with recent meta-analyses (Cao et al., 2023) and longitudinal studies (Gao et al., 2023; Li et al., 2023; Motoc et al., 2023; Nobile et al., 2023; Sui et al., 2023; Yang et al., 2023; Zare Sakhvidi et al., 2022). Inhaled fine particulate matter from air pollution can enter the bloodstream and breach the blood/brain barrier. This process may trigger systemic oxidative stress and inflammation (Genc et al., 2012; Valavanidis et al., 2008), which contributes to the development of mental health problems (Anisman and Hayley,

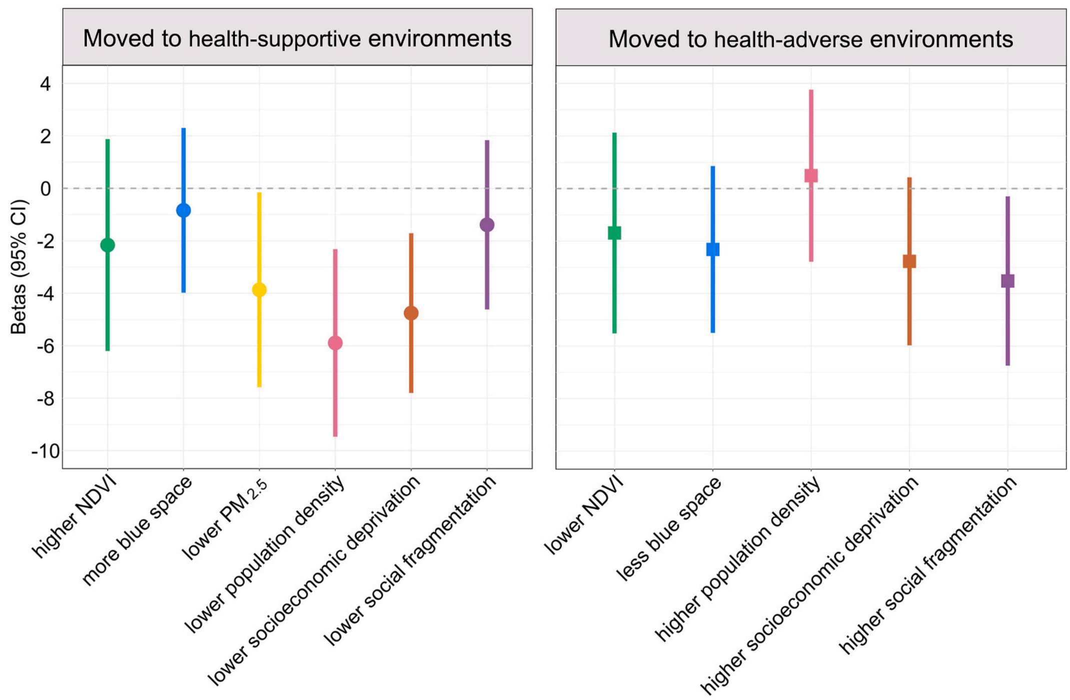

Fig. 3. Difference-in-difference regression estimates of moving into health-supportive and health-adverse neighborhood-based environmental exposures on MHI-5 scores with 95% confidence intervals (CI). Model adjustments were by age, marital status, household type, employment status, highest education level, household net income level, NDVI, blue space, $PM_{2.5}$, population density, socioeconomic deprivation, and social fragmentation. Estimates for each association were created by fitting a separate model. A health-supportive relocation occurred when there was a ≥10% increase in NDVI or blue space, a ≥10% decrease in $PM_{2.5,}$ population density, socioeconomic deprivation, or social fragmentation. A health-adverse relocation was a ≥10% decrease in NDVI or blue space, a ≥10% increase in $PM_{2.5,}$ population density, socioeconomic deprivation, or social fragmentation. Data source: Longitudinal Internet Studies for the Social Sciences panel; Landsat images in Google Earth Engine; Satellite-derived $PM_{2.5}$ European Regional Estimates (V4.EU.03); Statistics Netherlands; Dutch population register.

2012; Barron et al., 2017).

Moving to a less socioeconomically deprived neighborhood was associated with improved mental health. This result is congruent with meta-analytical (Richardson et al., 2015; Sui et al., 2022) and longitudinal findings (Boje-Kovacs et al., 2023; Graif et al., 2016; Nguyen et al., 2023; White et al., 2017). One possible explanation is that people residing in socioeconomically deprived neighborhoods tend to be more frequently exposed to risk factors such as crime, noise, and disorder. These adverse exposures elevate the stress level, which, in turn, negatively affects mental health (Graif et al., 2016; Sui et al., 2022).

The longitudinal evidence based on neighborhood population density and mental health is conflicting. Higher neighborhood population density was associated with a higher risk of developing mental illness in Sweden (Sundquist et al., 2004; Tarkiainen et al., 2021) and Finland (Tarkiainen et al., 2021), while the association was null in an Italian (Tarkiainen et al., 2021) and Dutch study (Sui et al., 2023). As an environmental determinant, population density is a complex metric subsuming other neighborhood physical and social characteristics (Motoc et al., 2023; Walters et al., 2011). Highly populated areas typically face pronounced noise and crime (Freeman, 1984; Peen et al., 2010; Zijlema et al., 2015). Additional adverse factors found in highly dense areas include lower availability of social and leisure facilities (e.g., parks) and a tendency to overcrowding (Mitrany, 2005). These factors, cumulatively, may lead to perceived urban stress (Beenackers et al., 2018), which can put people at increased risk for mental illness.

The findings concerning the mental health association of social fragmentation are limited and inconsistent. Our results showed that increases in neighborhood social fragmentation were positively associated with mental health. We are aware of only two other longitudinal studies that have examined associations between neighborhood social fragmentation and adults' mental health. In a study of British civil servants, Stafford et al. (2008) found that more fragmented neighborhoods were associated with poorer mental health. By contrast, Sui et al. (2023) found null associations between changes in neighborhood social fragmentation and adult mental health changes in the Dutch context. Other health associations with social fragmentation were also ambivalent. Hagedoorn et al. (2020), for example, found lower suicide risk in more fragmented neighborhoods for middle-aged male and short-term residents. It was demonstrated by Collings et al. (2009) that a U-shaped relationship between neighborhood social fragmentation and suicide - living in either the most or the least fragmented neighborhoods was associated with an elevated suicide rate compared to living in neighborhoods with intermediate levels of fragmentation. However, conclusions on the health impacts of social fragmentation and the mechanisms at play will require more longitudinal research.

We found that neighborhood green and blue spaces, after relocation, showed non-significant associations with mental health, which is in line with previous longitudinal studies (Mouly et al., 2023; van den Bosch et al., 2015; Weimann et al., 2015) and meta-analyses (Sui et al., 2022). By contrast, some studies did find mental health benefits related to increased neighborhood green spaces (Alcock et al., 2014, 2015). One possible reason for such conflicting findings is that our measurements (i.e., NDVI and NDWI) could only capture neighborhoods' overall green and blue spaces, which cannot examine associations between specific types of vegetation or water land cover and mental health.

4.3. *Strengths and limitations*

To our knowledge, this is the first study to examine associations between multiple physical and social neighborhood environments and mental health following residential relocation. A methodological strength is that we rigorously minimized the confounding using cutting-edge econometric modeling strategies (Heckman et al., 1997, 1998). Propensity score matching allowed us to adequately reduce observed confounders (Brookhart et al., 2006; Cuong, 2013), while our difference-in-difference approach controlled for unobserved time-invariant confounders in the regression (Donald and Lang, 2007). Unlike previous studies (Alcock et al., 2015, 2014; Mouly et al., 2023; Nguyen et al., 2023; van den Bosch et al., 2015), we also accounted for adults' baseline mental health status to address possible residential self-selection (Hooper et al., 2020). Finally, we considered time-varying factors related to mental health following residential relocation (e.g., life events, co-occurred environmental exposure) rather than treating them as time-invariant as done elsewhere (Chen et al., 2021; Chiu et al., 2016).

Despite these strengths, we must acknowledge some limitations. First, although we included movers across four waves to increase the sample size, our findings perforce relied on a moderately sized sample. Approximately half of those who relocated had follow-up attrition, which may challenge the generalization of our findings to the Dutch population. In addition, the sample size of non-movers significantly shrinks after using the propensity score matching, but it comes with methodological benefits (i.e., mitigating the observed differences between the control and the study group).

Second, despite our rich panel data, some life events related to moving were unavailable. We can thus not exclude that these unmeasured time-varying confounding effects were at play (Curnock et al., 2016). For example, respondents did not report whether they changed workplaces the year before moving. As compensation, we controlled for change in employment status, which likely has mental health effects (Braun et al., 2016; Paul and Moser, 2009).

Third, we only included movers with at least a 10% change in their exposure levels between pre- and post-moving. There is no gold standard in the literature; thus, our threshold value was chosen ad hoc, representing a compromise between sample size and exposure changes. We cannot rule out that another operationalization may affect the environmental health associations.

Finally, since we assessed the exposures at the level of postal code areas rather than residential addresses, some exposure misclassifications are likely and the reported associations may also be subject to the modifiable areal unit problem (Flowerdew et al., 2008); however, in another Dutch study, the environment-health associations remained broadly similar using buffers and postal code areas (Helbich et al., 2021).

5. Conclusions

This study used residential relocation to assess to what extent changes in environmental exposures are longitudinally associated with mental health. Our findings suggested that moving to less air-polluted, less densely populated, less socioeconomically deprived, and more fragmented neighborhoods was associated with improved mental health. We observed null associations for changes in green space and blue space. More experimental studies are warranted to verify our findings and further establish the longitudinal effects of the residential environment on mental health.

CRediT authorship contribution statement

Yuwen Sui: Writing – original draft, Visualization, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Dick Ettema:** Writing – review & editing, Supervision. **Marco Helbich:** Writing – review & editing, Supervision, Data curation, Conceptualization.

Declaration of AI tools

No generative AI and AI-assisted technologies were used during the preparation of this work.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2024.120481.

Data availability

The authors do not have permission to share data.

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