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Cardiometabolic Profiles and Change in Neighborhood Food and Built Environment Among Older Adults: A Natural Experiment.

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Abstract

Background: The association between neighborhood environment and health may be biased due to confounding by residential self-selection. The displacement of disaster victims can act as a natural experiment that exposes residents to neighborhood environments they did not select, allowing for the study of neighborhood effects on health.

Methods: We leveraged data from a cohort of older adults aged 65 years or older living in Iwanuma, Japan, located 80 km west of the 2011 Great East Japan Earthquake and Tsunami. Surveys were conducted 7 months before the disaster, as well as 2.5 and 5.5 years afterwards, and

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Data and Code Availability: Data used in this study will be made available upon request, as per NIH data access policies. The authors require the applicant to submit an analysis proposal to be reviewed by an internal JAGES committee to avoid duplication. Confidentiality concerns prevent us from depositing our data in a public repository. Authors requesting access to the Iwanuma data need to contact the principal investigator of the parent cohort (K.K.) and the Iwanuma substudy principal investigator (I.K.) in writing. If approval to access the data is granted, the JAGES researchers will request the outside investigator to help financially support our data manager's time to prepare the data for outside use. Computing code used in this study will be made available by the corresponding author (K.S.) upon request.

linked with medical records. We classified each individual’s type of exposure to neighborhood environment based on proximity to local food and recreation destinations and walkability.

Results: Fixed-effect models indicated that change in the exposure type from low to high urban density was associated with increased body mass index (0.46 kg/m^2, 95% CI: 0.20 to 0.73), waist circumference (1.8 cm, 95% CI: 0.56 to 3.0), low-density lipoprotein cholesterol (11 mg/dL, 95% CI: 5.0 to 17), and decreased high-density lipoprotein cholesterol (−3.1 mg/dL, 95% CI: −5.0 to −1.3). We observed similar trends when we analyzed only the individuals who experienced post-disaster relocation to temporary homes.

Conclusions: Increased proximity to food outlets was simultaneously correlated with greater walkability and accessibility to recreational destinations; however, any protective association of physical activity-promoting built environment appeared to be offset by proximity to unhealthy food outlets, especially fast food restaurants and bars.

Keywords

Neighborhood; Food Environment; Built-environment; Cardiometabolic Profiles; Longitudinal Studies; Natural Experiment

Introduction

An extensive evidence base has accumulated during the past 2 decades suggesting that neighborhood environments affect residents’ health behaviors and chronic disease risk. (1–3) For example, although evidence is still mixed, many studies have demonstrated that food-environment (e.g. access to food outlets offering calorie-dense meals) and built-environment (e.g. neighborhood walkability) influence people’s cardiovascular risks by shaping their dietary intake and physical activity levels. (1, 3–6) Understanding the relationship between neighborhood environment and health among older adults is important because studies suggest that residential contexts may be particularly relevant to the health of this population, for example because older adults spend more of their daily lives in their neighborhoods relative to working-age populations. (7) However, two fundamental methodological challenges have hampered causal inference in studies linking neighborhood environment to health.

First, self-selection of residential location can produce confounding bias. (8–10) Exposure to neighborhood environments often reflects the otherwise unmeasured health preferences of residents. For example, residents who are concerned about healthy nutrition may not move to neighborhoods with abundant fast food outlets. Randomly assigning neighborhood exposures is expensive or ethically infeasible; hence, researchers must rely upon natural experiments, such as studying changes in dietary habits following a new supermarket opening. (11) However, even the opening of new stores is subject to confounding, since businesses will tend to open in neighborhoods where the owners believe they will make a profit.

Secondly, neighborhood features tend to be highly clustered, making it a challenge to disentangle the effects of specific characteristics. For example, proximity to the nearest fast food establishment may be highly correlated with supermarkets, or even walkability (e.g.

intersection density). The traditional approach of covariate adjustment can result in unstable estimates and inference due to multicollinearity. (12, 13) Independent variation in the exposure variable is further reduced within covariate strata when the clustered environmental characteristics are modeled simultaneously, increasing reliance on model-based extrapolation. (10, 14)

In the present study we sought to overcome these methodologic challenges by taking advantage of a unique natural experiment stemming from the 2011 Great East Japan Earthquake in which exogenous changes in residential location occurred due to the resettlement of older survivors into temporary housing after their homes were damaged/ destroyed by the tsunami. A particular strength of our cohort study is that the baseline was established 7 months prior to the disaster. Thus, we have a rich set of data for participants that predates the disaster. In addition, we sought to holistically assess patterns of multiple neighborhood characteristics and their associations with health outcomes, rather than focusing on any single dimension of the neighborhood environment. (12, 15–17)

Methods

Data

We used data from the Japan Gerontological Evaluation Study (JAGES), a nationwide cohort study of Japanese older adults aged 65 years or older, established in 2010 with the aim of studying the social determinants of healthy aging. (18, 19) Notably, the baseline survey wave of JAGES was completed in 2010, 7 months prior to the 2011 Great East Japan Earthquake & Tsunami.

One of the field sites of the JAGES cohort was in Iwanuma City, Miyagi Prefecture, located approximately 80 km (128 miles) west of the earthquake epicenter. The total population of Iwanuma was 44,187 in 2010. (20) JAGES conducted a census of all residents aged 65 years or older (n = 8,576) in August 2010, and obtained valid responses from a total of 4,957 residents (Response rate = 58%) after excluding non-respondents (n = 3,518) and those with invalid identifying information (n = 101). In the case of the latter, there was high suspicion that someone other than the respondent (e.g. another household member) had filled out the mailed survey.

The Great East Japan Earthquake (the Richter scale: 9.0), occurred on March 11th, 2011. The subsequent tsunami resulting from the earthquake caused devastating damage to Iwanuma and other coastal areas of northeastern Japan. The tsunami killed 180 residents, damaged 5,542 houses, and inundated 48% of the land area in Iwanuma (Figure 1). (21)

Two follow-up survey waves have been conducted in the aftermath of the disaster, in 2013 and 2016. During the follow-up period, the surviving cohort participants whose homes were damaged or destroyed by the tsunami experienced two occasions on which large-scale exogenous change in residential location occurred. First, soon after the disaster onset, survivors were moved into temporary trailer homes built by the city (kasetsu jutaku) or into subsidized apartments on the private rental market (minashi kasetsu). Although the survivors whose homes were severely damaged or destroyed could choose other types of relocation (e.g. building a new home at their own expense), the majority of the survivors chose these two types of temporary accommodation for their low financial burden. Specifically, among the participants who lost their homes (n = 159), 67% (n=107) took advantage of the opportunity to move to these units. Both types of temporary housing were located in the densely populated areas of the city. Second, the trailer home village was closed down by the city and the subsidy for apartments on the private rental market ended in April 2016, and the evacuees living in these temporary homes were moved into permanent housing built by the city, located approximately 4km further away from the city center (Figure 1).

In October 2013, approximately 2.5 years after the disaster onset, JAGES identified the addresses of 99.7% of the original sample and conducted the follow-up survey of all survivors from the baseline cohort. Of the 4,380 eligible survivors who were healthy enough to participate and lived in Iwanuma at the time of follow-up, 3,567 responded to the mailed questionnaire (follow-up rate = 81%), in which personal experiences of natural disaster were assessed. A total of 131 participants whose homes were damaged (n = 24) or destroyed (n = 107) reported they experienced post-disaster relocation to temporary housing in the aftermath of the earthquake. In November 2016, we conducted the third wave of survey and re-contacted all respondents of the previous wave. Of the 3,323 eligible study participants, we obtained responses from 2,781 subjects. See eFigure 1 for the flow chart of survey sample selection.

We then linked the panel survey data to medical record data from annual regular health checkups conducted by Iwanuma city, which contains information about participants' objectively measured cardiometabolic profiles. Under the Japanese National Health Insurance system (Kokuho), municipalities provide health checkups annually (Tokutei Kenshin) and older adults can participate in the checkups voluntarily. (22) After exclusion of observations from persons who did not participate in the health checkup at each wave, we obtained the analytic sample of 4,542 person–wave observations. (23) Of the whole analytic sample, 141 person–wave observations were from those who experienced post-disaster relocation to temporary housing (Figure 2).

Measurements

Outcome—Our outcome of interest was a series of objectively measured cardiometabolic profiles including systolic and diastolic blood pressure (mm Hg), body mass index (BMI;kg/m^2), waist circumference (cm), high-density lipoprotein cholesterol (HDL; mg/dL), low-density lipoprotein cholesterol (LDL; mg/dL), and triglyceride (mg/dL) measured in June 2010, 2013, and 2017. We used data from 2017 to secure a sufficient time interval between outcome measurement and the second relocation from temporary to permanent homes in April 2016. Waist circumference was measured only among persons under age 75 years. Systolic and diastolic blood pressure, BMI, and waist circumference were measured by public health nurses at the health check-ups. Serum levels of biomarkers (i.e. HDL, LDL, and triglyceride) were measured using blood samples collected during the same check-ups.

Exposure—Our exposure of interest was type of individual's exposure to neighborhood food- and built-environment around their homes. We performed a holistic assessment of patterns in individual's exposure to multiple neighborhood food- and built-environment features. Food environment was defined based on proximity to local food outlets from one's home address. The home address of each participant in each study wave was identified using the official residential register and geocoded by Google Maps Application Programming Interface. Based on the corporate telephone directories provided by Nippon Telegraph and Telephone Corporation, we additionally obtained address information of all business facilities in Iwanuma and Natori, the closest neighboring city geographically accessible from Iwanuma, in each study wave. Using the Origin-Destination matrix feature of ArcGIS Desktop version 10.7.1 (Esri, Redlands, California, USA), we calculated the road network distance from each home address to the nearest bar, full-service restaurant, convenience store, supermarket, fast-food restaurant, and fresh food store.

Built environment was defined based on proximity to the nearest facilities hypothesized to affect one's physical activity level and cardiometabolic profiles, as well as walkability around each respondent's home address.(1, 4) Using the same approach for food environment, we calculated proximity to the nearest park, healthcare facility, sports facility, and *pachinko* parlor from one's home address. (*Pachinko* is a popular recreational gaming facility in Japan, where people typically spend hours sitting in front of mechanical gaming machines, and is hence a potential driver of sedentary behavior.) (24) Following prior studies on walkability in Japan, we assessed the walkability of a street network-based 500-m buffer around each respondent's home address based on population density, intersection density, and availability of local destinations (see eAppendix 1 for more detailed description of how walkability was operationalized in this study). (25–27)

Using the proximity to local food and recreation destinations, as well as walkability scores, we performed Gaussian mixture modeling (a.k.a. latent profile analysis) to identify unobservable latent patterns of respondents' joint exposure to food outlets and built-environment features. (28) See eAppendix 2 for more description of this approach. The resulting three classes were labeled "Low", "Middle", and "High" urban density based on average proximity to food and recreation destinations and walkability within each class (Table 1). The geographical distribution of each environmental feature and the exposure type classification are shown in eFigure 3 and Figure 3, respectively. We also presented a correlation matrix of proximity to each destination and walkability in eFigure 4.

Covariates—As potential time-varying confounders, we controlled for age, household income, marital status, working status, depressive symptoms, instrumental activities of daily living (IADL), and treatment for major diseases including hypertension, diabetes, stroke, and dyslipidemia. Annual household income was equivalized in order to adjust for difference in household size. We created binary indicators for marital status (married vs divorced/widowed/single) and working status (current working vs not working). Depressive symptoms were assessed using the 15-item Geriatric Depression Scale, a commonly used screening tool for depression among older adults, where higher scores indicate more depressive symptoms. The Japanese version of the scale has been shown to have high reliability and validity (29). Instrumental activities of daily living, which captures physical, cognitive, and social independence of older adults, was measured by the 13-item Tokyo Metropolitan Institute of Gerontology Index of Competence. (30–32) Four binary variables were created based on self-reported current medical treatment for hypertension, diabetes, stroke, and dyslipidemia.

Statistical Analysis—To take advantage of the rich panel data structure from three waves, we used a fixed-effects regression approach in this study. (33) By estimating associations between type of individual's exposure to neighborhood food- and built-environment around home and cardiometabolic profiles using longitudinal within-individual variation, this method can eliminate confounding bias due to all observed and unobserved time-invariant covariates (such as genetic characteristics) in addition to observed time-varying confounders. The regression model we fitted is represented by the following equation.

$$Y_{it} = \beta_1 A_{it} + C_{it}\beta + \alpha i + \in_{it}$$

where Y_{it} is a cardiometabolic profile of individual i on wave t; A_{it} is type of individual's exposure to neighborhood food- and built-environment around home; C_{it} is a vector of time-varying covariates; and α_i is the individual fixed-effect that controls for all time-invariant factors. Associations from the fixed-effect analyses can be interpreted as the relationships between within-individual *changes* in the exposure and the outcomes.

Multiple imputation for missing data in covariates was performed using the R package Amelia II, which is based on bootstrapping-based algorithm and appropriately handles missing data imputation of panel data (34). After generating 20 imputed datasets, we performed the fixed effects regression using each imputed dataset and combined the results across imputations (see eAppendix 3 for the R code).

We performed analyses using three samples; the whole panel (4,542 person–wave observations), the displaced individuals who experienced post-disaster relocation to temporary housing (141 person–wave observations), and non-displaced individuals who did not move to temporary housing (4,430 person–wave observations). Using the displaced sample reduces susceptibility to bias due to unobserved time-varying confounders (e.g. changes in preference of residential location). We also used the non-displaced sample to check whether the results from the whole sample are robust to exclusion of the displaced (see eAppendix 4 for the rationale). We computed cluster robust standard errors for statistical inference. (35)

Based on previous studies reporting heterogeneous health effects of neighborhood environment by gender, we performed gender-stratified analyses to examine the potential effect modification by gender. (36–40) Furthermore, to see if the results are robust to the choice of the number of classes to be derived from our Gaussian mixture model, we repeated the same analyses using a 2-class and a 4-class solution. The geographic distributions of these classes are shown in eFigure 5 and eFigure 6.

The survey protocol was approved by the human subjects' committee of the Harvard T.H. Chan School of Public Health (CR-23143) as well as the human subjects' committees of Tohoku University (21-40, 24-29), Nihon Fukushi University (10-05, 13-14), and Chiba University (2493). Informed consent was obtained at the time of data collection.

Results

Baseline demographic characteristics of the participants, including sex, age, marital status, and working status, were comparable to those from the census of older residents in Iwanuma (eTable 1). Moreover, baseline participants and those who participated in at least one of the two follow-up surveys (and thus contributed to the fixed-effect models) were similar in their characteristics (eTable 1). Table 2 describes the demographic characteristics of the analytic sample by year and displacement status. Almost all of the displaced individuals (98%) were exposed to low urban density prior to the disaster and most of them (80%) moved into the inland area with high urban density where temporary shelters were located in 2013. In 2016, a majority of these individuals (82%) moved into permanent homes built in a new location with low urban density. The displaced individuals experienced changes in some covariates over time (e.g., decrease in household income and increase in depressive symptoms after the disaster) while such changes were not observed among the non-displaced individuals.

Figure 4 (see eTable 2 and eTable 3 for the full results) shows point estimates and confidence intervals for the associations between neighborhood exposure types and cardiometabolic profiles from the adjusted fixed-effect regression models. When the whole sample (4,542 person–wave observations) was analyzed, we found evidence that change in the type of exposure to neighborhood food and recreation destinations/walkability from low to middle/high urban density was associated with increased BMI (0.39 kg/m^2, 95% CI: 0.11 to 0.67 for middle; 0.46 kg/m^{2,} 95% CI: 0.20 to 0.73 for high), waist circumference (1.7 cm, 95% CI: 0.39 to 3.0 for middle; 1.8 cm, 95% CI: 0.56 to 3.0 for high), and LDL cholesterol (5.9 mg/dL, 95% CI: −0.15 to 12 for middle; 11 mg/dL, 95% CI: 5.0 to 17 for high), and decreased HDL cholesterol (−3.7 mg/dL, 95% CI: −5.7 to −1.8 for middle; −3.1 mg/dL, 95% CI: −5.0 to −1.3 for high). The associations with deteriorated BMI, HDL cholesterol, and LDL cholesterol remained evident for the high (0.63 kg/m^2, 95% CI: 0.13 to 1.1 for BMI; −3.5 mg/dL, 95% CI: −6.2 to −0.81 for HDL; and 8.8 mg/dL, 95% CI: 1.9 to 16 for LDL) but not for the middle urban density (−0.12 kg/m2, 95% CI: −1.4 to 1.2 for BMI; −0.72 mg/dL, 95% CI: −8.2 to 6.8 for HDL; and −19 mg/dL, 95% CI: −36 to 2.0 for LDL) when we analyzed the displaced individuals only (i.e. for whom changes in exposure levels are expected to be exogenous). In the analyses using the non-displaced sample, change in the type of exposure to neighborhood destinations/walkability from low to high urban density was associated with decreased HDL cholesterol and increased LDL cholesterol. Gender-stratified analyses showed similar trends that high (vs low) urban density was overall associated with increased cardiovascular risks. However, the associations with BMI and triglyceride were evident only among women. When we changed the number of classes for the exposure variable, we found a similar trend such that changes in the exposure class from low to higher urban density were associated with unhealthy cardiometabolic profiles (eFigure 7 and eFigure 8).

Discussion

This study aimed to demonstrate the potential impact of exposure to neighborhood environment on objectively measured cardiometabolic profiles among older adults, using a typological approach to characterize pattern of exposure to neighborhood environment as well as rigorous control of confounding using panel data fixed-effects analysis and exogenous changes in residential locations stemming from the unique natural experiment setting. Our results indicate that change in the type of exposure to neighborhood destinations/walkability from low to middle/high urban density was associated with unhealthy cardiometabolic profiles among older adults. The findings were robust to the control for confounding using post-disaster exogenous changes in residential locations in addition to adjustment of all time-invariant and observed time-varying confounders by fixed-effects analysis.

The natural experiment design to deal with the potential bias due to self-selection into neighborhoods has been previously used in other studies. (1) Notably, a study of approximately 61,000 refugees who were resettled in Sweden found that being quasi-randomly assigned to more deprived neighborhoods was associated with increased risk of diabetes. (41) These natural experiment studies of exogenous changes in residential address cannot estimate the effect of a hypothetical intervention to modify a specific neighborhood feature, but they estimate the effect of relocating people to different types of neighborhoods. The potential effects of relocating people have been also demonstrated in randomized trials (e.g. Moving to Opportunity experiment) (42) In the present study, we sought to make a contribution to the existing literature by combining the natural experimental design with the typology approach to holistically characterize neighborhoods rather than looking at a single neighborhood feature such as proximity to a specific retail outlet.

Notably, the class of high/middle urban density (vs low urban density) was characterized not only by proximity to unhealthy food outlets but also environmental features that have been shown to promote health: namely, closer distance to physical activity facilities and parks and high walkability. (4, 25, 26) In other words, environmental features of neighborhoods in Iwanuma City – both the healthy and unhealthy– are clustered together. Health tradeoffs associated with different types of urban form are well documented, for example with urban environments promoting physical activity but also increasing exposure to air pollution. (43)

The overall health effects of the accessibility urban environments provide to both healthy and unhealthy resources is poorly understood, underscoring the importance of our study. To our knowledge, this question has been investigated in only one previous study. DeWeese *et al* found that living in a neighborhood with high density of unhealthy food stores was associated with increased overweight/obesity despite the higher prevalence of physical activity facilities in the neighborhood, which is consistent with the finding in our cohort of older disaster survivors. (17) One explanation of these findings is that adverse effect of proximity to unhealthy food outlets outweighs the benefit of physical activity-promoting built environment, resulting in a net unfavorable impact on cardiometabolic profiles.

To demonstrate utility of the typological approach for neighborhood characterization, we performed a secondary analysis using the conventional approach of modeling changes in proximity to specific local food and recreational destinations and walkability (see eAppendix 5). The results of the sensitivity analysis indicated the importance of the typological approach for holistic assessment of neighborhood environment.

We found some evidence of effect modification by gender. We found that exposure to high urban density was associated with increased BMI only among women. Past studies have consistently found that women may be more strongly influenced by neighborhood environment. (38–40) For instance, Wang *et al.* demonstrated that higher neighborhood density of small grocery stores was linked to increased BMI only among women. (39) One possible explanation is that women may spend more time in their neighborhood and therefore have a higher exposure to neighborhood factors because of their low labor force participation and more frequent social participation. (38) Indeed, in our Iwanuma sample, women were less likely than men to be working and more likely to meet their friends often (eTable 4). Further studies are needed to explore why such gender-based heterogeneity in effects of neighborhood environment exists.

Several limitations should be noted. First, most local food and recreation destinations were geographically clustered in one location in Iwanuma. Thus, the “high urban density” was characterized by closer distance to all the local destinations as well as high walkability compared to the “low urban density” group. Thus, the classes were distinct in all the observed neighborhood features, and we were not able to identify which aspect of the exposure to high urban density was particularly toxic. The issue of geographically clustering neighborhood features is not just unique to the current study, but it is a problem inherent in virtually all neighborhood research examining urban geography that exists in the real world. (12, 16, 17) One approach to disentangling the effects of correlated neighborhood characteristics is to conduct natural experiment studies of changes in a single feature of neighborhood (e.g. a new supermarket opening). (11) However, such changes in neighborhood are likely to be endogenous. For instance, a new supermarket opening may be associated with increased fruit and vegetable consumption because a supermarket chain seeks to open a new store when and where there is a demand of healthy foods. We took advantage of exogenous changes in residential location and solved this endogeneity problem. Moreover, studying changes in a single feature of neighborhood ignores the complex interactions between diverse neighborhood features. While our study, as is the case for other studies of exogenous changes in residential address including randomized trials (e.g. Moving to Opportunity experiment), does not estimate the effect of a specific neighborhood feature, it estimates the effect of an intervention of relocating people to different types of neighborhoods, which may be more policy-relevant. (44)

Second, changes in residential location among the displaced sample are due to post-disaster relocation to or from temporary homes. It is possible that living in temporary homes itself has independent adverse impacts on cardiometabolic profiles due to its highly stressful environment (e.g., lack of privacy and cramped room). (45, 46) Thus, our effect estimates from this sample may be, to some extent, attributable to their experiences unique to disaster victims rather than changes in exposure to neighborhood environment. However, we performed sensitivity analyses excluding the displaced individuals too and still found evidence that change in the exposure type from low to high urban density was linked to deteriorated cardiometabolic profiles.

Lastly, the current study was based on a specific population (i.e., older adult survivors affected by the 2011 Great East Japan Earthquake) and, thus, generalizability of our findings to other groups may be limited. Specifically, our findings may not be generalizable to other populations when distributions of effect modifiers are different across populations. (47) For example, older adults may be more dependent on the immediate residential neighborhood environment due to declines in physical and cognitive functioning and, thus, the magnitude of neighborhood effects may be smaller in younger populations than our estimates. (7)

Some other limitations are discussed in eAppendix 6 due to limited space.

In conclusion, our natural experiment study demonstrated that exposure to neighborhood environment with high urban density characterized by closer distance to local food and recreation destinations and high walkability was associated with unhealthy cardiometabolic profiles among Japanese older adults, especially among women. Although our study could not identify what aspect of such exposure was particularly “toxic”, our findings, taken in context with the existing literature, are consistent with the hypothesis that greater proximity to unhealthy food outlets may have a net adverse impact on cardiometabolic profiles, even if the move is simultaneously accompanied by improved physical activity-promoting built environment. However, future studies with a richer set of information on levels of dietary intakes and physical activities are warranted to examine the underlying mechanism.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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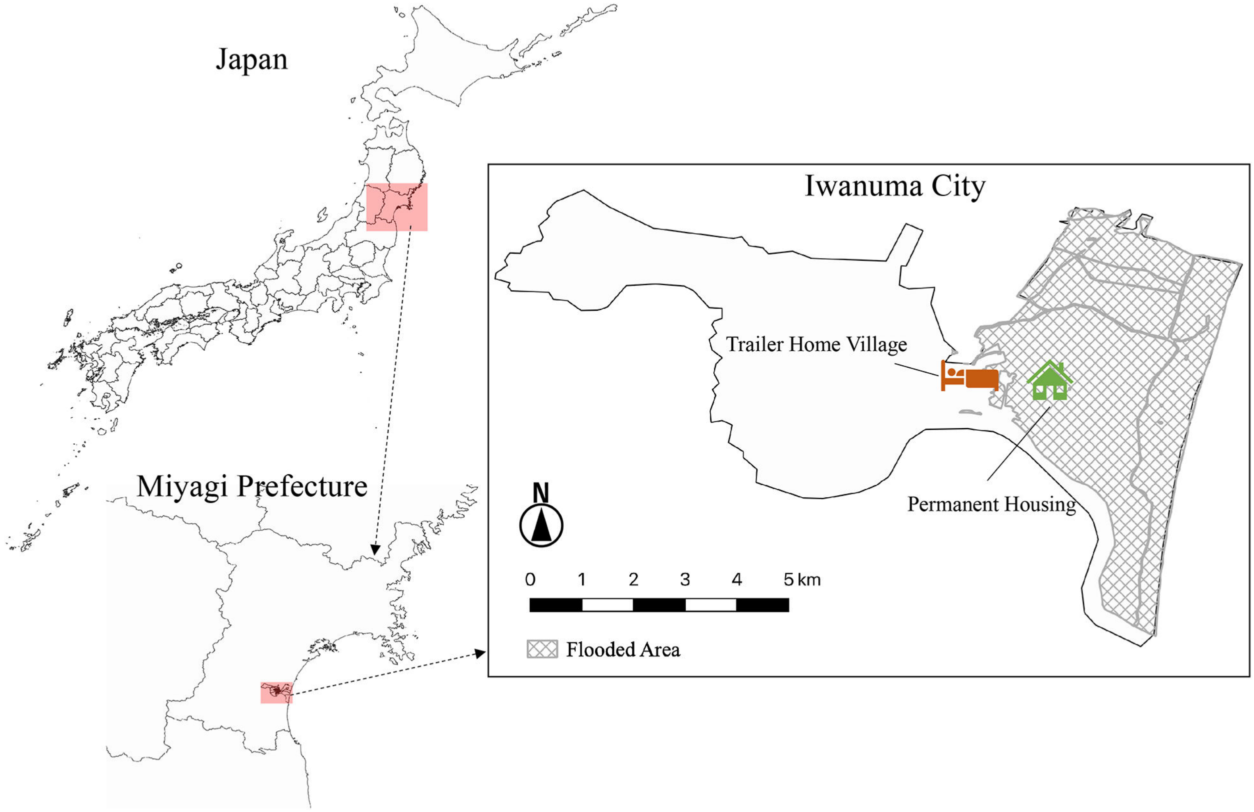

Figure 1.
Map of Iwanuma City, Miyagi Prefecture, Japan

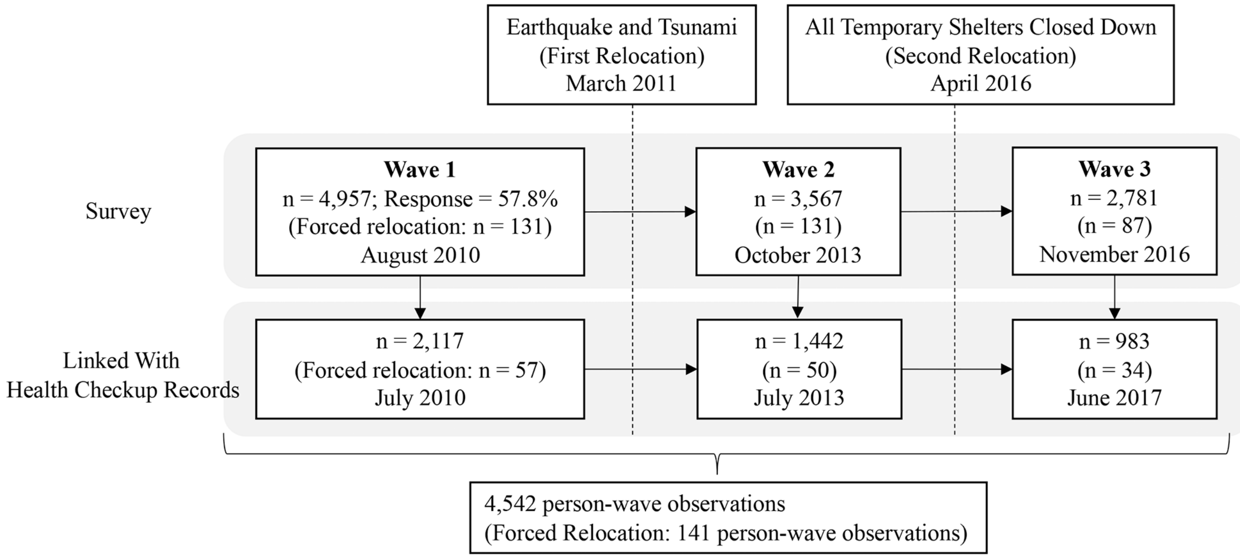

Figure 2.
Flow Chart of the Analytical Sample Selection.

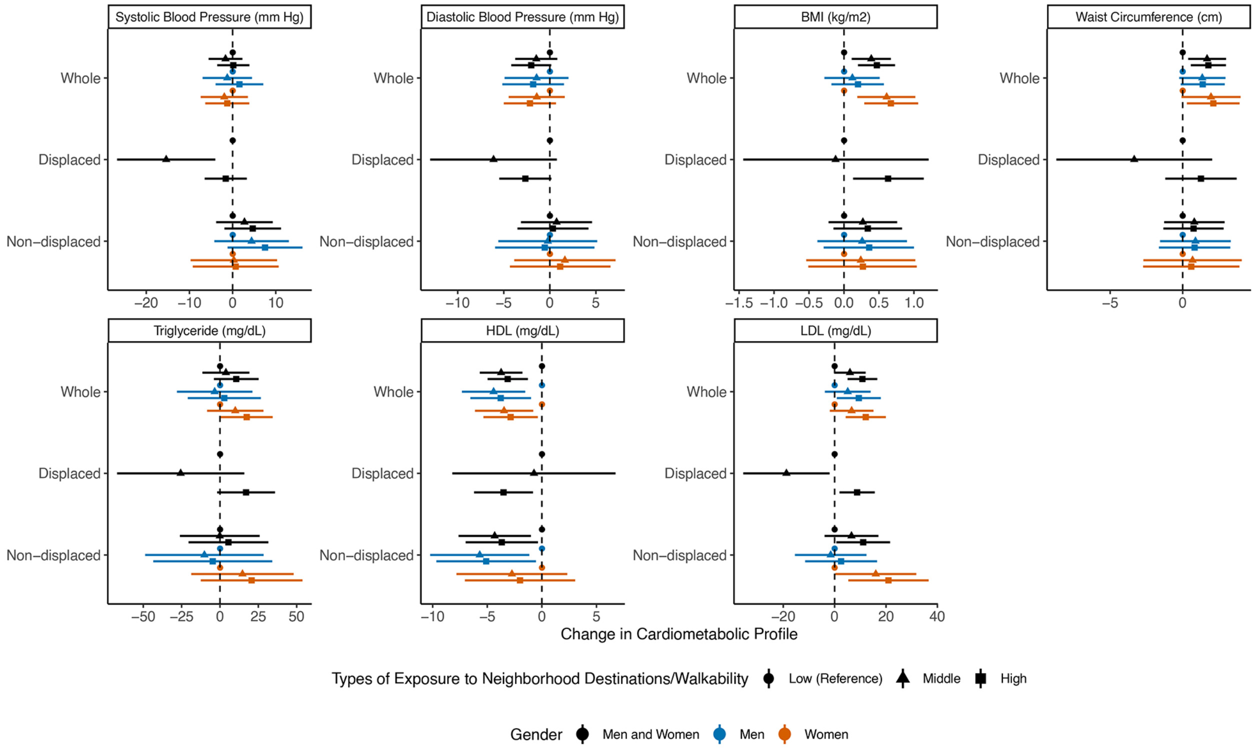

Figure 3.

Distribution of the Types of Exposure to Neighborhood Environment Among (A) the Whole Sample and (B) the Displaced Before and After the 2011 Great East Japan Earthquake.

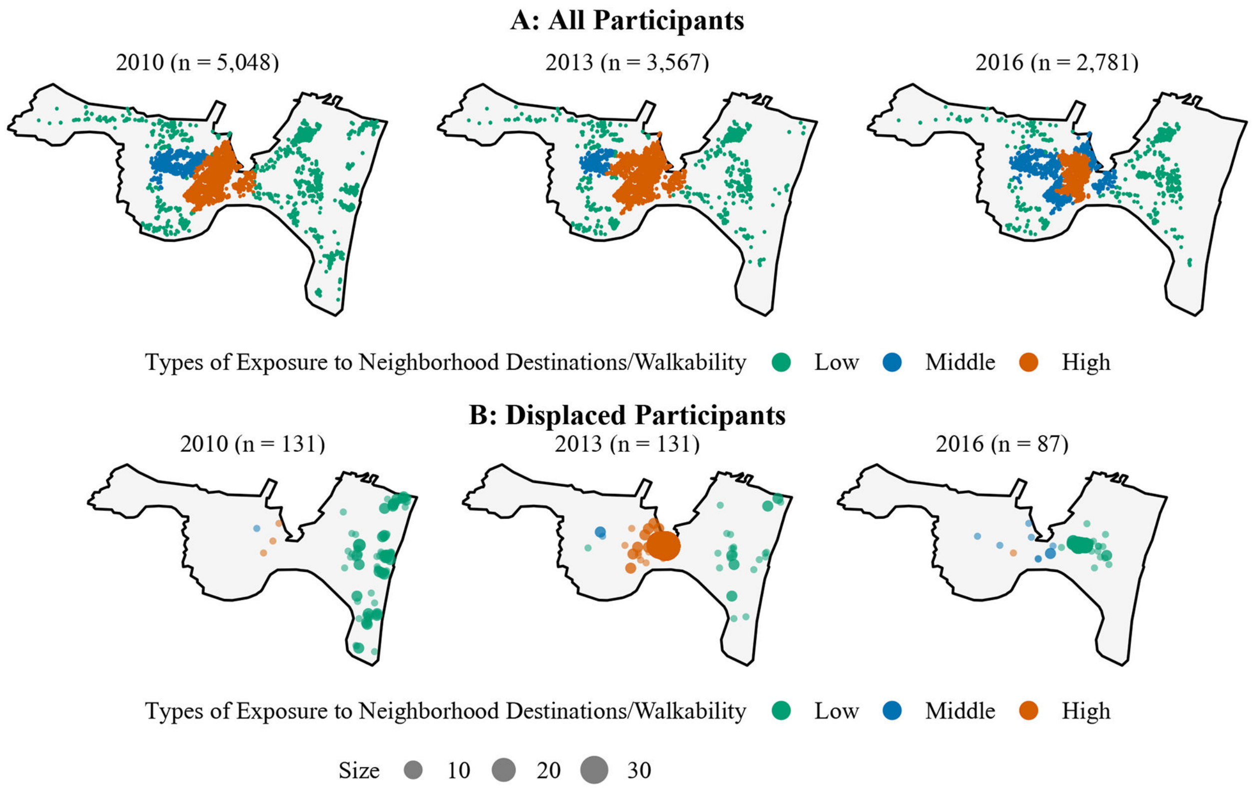

Figure 4.

Fixed-effect Estimates for Associations Between Changes in Cardiometabolic Profiles and Changes in Types of Exposure to Neighborhood Environment.

Models were adjusted for all time invariant and observed time-varying confounders including age, household income, marital status, working status, depressive symptoms, instrumental activities of daily living (IADL), and treatment for major diseases (hypertension, diabetes, and dyslipidemia). We did not perform gender-stratified analysis using the displaced sample because the sample size was limited. Units of the outcomes were mmHg for systolic & diastolic blood pressure, kg/m^2 for body mass index (BMI), cm for waist circumference, and mg/dL for serum triglyceride, high-density lipoprotein cholesterol (HDL), and low-density lipoprotein cholesterol (LDL).

Table 1.

Mean Distance to the Nearest Local Destinations and Walkability by Exposure Classification and Year

	2010			2013			2016		
	Low	**Middle**	**High**	**Low**	**Middle**	**High**	**Low**	**Middle**	**High**
Nearest Distance (meters)[a]									
Convenience Store	1298	512	560	1306	587	488	1114	484	345
Bar	3712	644	428	3130	616	484	3112	688	338
Fastfood	1755	512	591	1569	558	583	1529	508	457
Supermarket	1901	657	692	2192	1385	683	1727	880	615
Restaurant	1345	393	287	1288	407	348	1171	465	254
Fresh Food	1960	1560	447	1666	1933	552	1414	627	390
Park	949	261	319	959	214	316	935	251	371
Pachinko	3753	2491	926	3247	2918	1018	3047	1682	853
Sports Facility	2441	1463	1153	2368	1174	1199	2586	1387	1036
Healthcare	2205	731	586	1686	926	466	1506	671	372
Walkability[b]	−3.5	1.4	1.2	−3.8	1.1	1.0	−3.7	0.49	1.6

[a]Distance from home address to each destination was calculated based on road network distance

[b]Walkability of a street network-based 500-m buffer around each respondent's home address based on population density, intersection density, and availability of local destinations. We standardized each of the three components of walkability and calculated their sum as an individual's walkability score.

Table 2.

Characteristics of Study Participants Linked with Health Check-up Records by Year and Displacement S tatus (n = 2117)

	Displaced			Non-displaced		
	2010	**2013**	**2016**	**2010**	**2013**	**2016**
	n (%)	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**
Total	57 (100%)	50 (100%)	34 (100%)	1630 (100%)	1364 (100%)	930 (100%)
Neighborhood Environment						
Low urban density	56 (98%)	9 (18%)	28 (82%)	326 (20%)	249 (18%)	155 (17%)
Medium urban density	0 (0%)	1 (2.0%)	6 (18%)	330 (20%)	164 (12%)	420 (45%)
High urban density	1 (1.8%)	40 (80%)	0 (0%)	974 (60%)	951 (70%)	355 (38%)
Gender						
Men	25 (44%)	21 (42%)	17 (50%)	803 (49%)	702 (52%)	486 (52%)
Women	32 (56%)	29 (58%)	17 (50%)	827 (51%)	662 (49%)	444 (48%)
Marital Status						
Single	11 (19%)	13 (26%)	8 (24%)	328 (20%)	284 (21%)	197 (21%)
Married	43 (75%)	36 (72%)	23 (68%)	1266 (78%)	1070 (78%)	705 (76%)
Missing	3 (5.3%)	1 (2.0%)	3 (8.8%)	36 (2.2%)	10 (0.7%)	28 (3.0%)
Job						
Not Working	39 (68%)	39 (78%)	17 (50%)	1259 (77%)	1156 (85%)	656 (71%)
Working	10 (18%)	7 (14%)	7 (21%)	224 (14%)	184 (14%)	119 (13%)
Missing	8 (14%)	4 (8.0%)	10 (29%)	147 (9.0%)	24 (1.8%)	155 (17%)
Hypertension Treatment						
No	31 (54%)	26 (52%)	18 (53%)	993 (61%)	791 (58%)	509 (55%)
Yes	25 (44%)	24 (48%)	16 (47%)	604 (37%)	573 (42%)	394 (42%)
Missing	1 (1.8%)	0 (0%)	0 (0%)	33 (2.0%)	0 (0%)	27 (2.9%)
Stroke Treatment						
No	56 (98%)	50 (100%)	34 (100%)	1570 (96%)	1321 (97%)	869 (93%)
Yes	0 (0%)	0 (0%)	0 (0%)	27 (1.7%)	43 (3.2%)	34 (3.7%)
Missing	1 (1.8%)	0 (0%)	0 (0%)	33 (2.0%)	0 (0%)	27 (2.9%)
Diabetes Treatment						
No	50 (88%)	45 (90%)	30 (88%)	1441 (88%)	1237 (91%)	813 (87%)
Yes	6 (11%)	5 (10%)	4 (12%)	156 (9.6%)	127 (9.3%)	90 (9.7%)
Missing	1 (1.8%)	0 (0%)	0 (0%)	33 (2.0%)	0 (0%)	27 (2.9%)
Dyslipidemia Treatment						
No	53 (93%)	46 (92%)	29 (85%)	1417 (87%)	1171 (86%)	760 (82%)
Yes	3 (5.3%)	4 (8.0%)	5 (15%)	180 (11%)	193 (14%)	143 (15%)
Missing	1 (1.8%)	0 (0%)	0 (0%)	33 (2.0%)	0 (0%)	27 (2.9%)
	Mean (SD)	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**
Age	72 (5.3)	74 (4.9)	75 (3.0)	72 (5.4)	75 (5.0)	77 (4.6)
Equivalized Household Income (10K yen)	180 (138)	139 (85.3)	162 (104)	231 (123)	226 (120)	224 (126)
IADL Score[a]	12 (1.3)	12 (1.0)	12 (1.2)	12 (1.3)	12 (1.6)	12 (1.5)

GDS Score[b]	3.5 (2.9)	4.6 (3.1)	2.3 (2.1)	3.1 (3.1)	2.9 (2.9)	2.6 (2.9)
Systolic Blood Pressure (mmHg)	129 (18)	130 (15)	132 (14)	131 (17)	133 (17)	133 (17)
Diastolic Blood Pressure (mmHg)	74 (11)	73 (9.0)	76 (8.7)	75 (10.4)	74 (10)	75 (11)
Body Mass Index (kg/m^2)	25 (3.1)	25 (3.0)	25 (3.2)	24 (3.1)	24 (3.2)	23 (3.1)
Waist Circumference (cm)[c]	85 (9.4)	87 (7.9)	88 (6.3)	85 (8.7)	85 (8.5)	85 (8.6)
Triglycerides (mg/dL)	117 (66)	132 (78)	108 (53)	121 (68)	122 (63)	120 (71)
HDL Cholesterol (mg/dL)[d]	60 (16)	57 (15)	62 (21)	59 (15)	61 (16)	61 (16)
LDL cholesterol (mg/dL)[e]	111 (26)	123 (29)	117 (26)	119 (28)	124 (29)	119 (28)

[a] Instrumental activities of daily living (IADL) was measured by the 13-item Tokyo Metropolitan Institute of Gerontology Index of Competence. Total score ranges from 0 to 13, where the higher score indicates more independence.

[b] Geriatric Depression Scale (GDS) score ranges from 0 to 15, where score indicates more depressive symptoms

[c] Waist circumference was measured only among persons under age 75 years

[d] High-density lipoprotein cholesterol

[e] Low-density lipoprotein cholesterol