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IZA DP No. 18251

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ABSTRACT

Uncovering the Biological Toll of Neighborhood Disorder Trajectories: New Evidence Using Machine Learning Methods and Biomarkers in Older Adults

This study examined the link between neighborhood disorder trajectories and metabolic and inflammatory biomarkers in U.S. older adults. We analyzed data from community-dwelling Medicare beneficiaries in the National Health and Aging Trends Study. Neighborhood physical disorder was assessed annually through interviewer observations over six years. Latent class analysis was used to identify exposure trajectory subgroups. Machine learning based inverse probability weighted (IPW) regression models were conducted to estimate associations with five biomarkers, including body mass index (BMI), waist circumference, hemoglobin A1C (HbA1c), high-sensitivity C-reactive protein (hsCRP), and interleukin-6 (IL-6). Compared to the stable low exposure group, older adults with increased exposure, decreased exposure, and stable high exposure exhibited higher levels of HbA1c. Only stable high exposure was associated with increased hsCRP. No significant associations were found for other biomarkers. Residential environments play an important role in shaping the biological risk of aging. Incorporating routine screening for neighborhood environmental risks and implementing community-level interventions are pivotal in promoting healthy aging in place.

JEL Classification: J14, I12, I14, R20, I18

Keywords: neighborhood disorder, metabolic and inflammation biomarkers, machine learning, inverse probability weighting, latent class analysis

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1. Introduction

As the number of older adults continues to increase, identifying factors that support healthy aging has become a critical public health priority. In response, the World Health Organization (WHO, 2023) has launched programs on age-friendly cities and communities to promote environments that foster autonomy, safety, and inclusion for older adults. Central to these initiatives is the recognition that residential contexts play a pivotal role in enabling older adults to age successfully in their homes and communities. At the same time, older adults are especially vulnerable to neighborhood environmental risks due to several age-related factors. They typically spend more time in their immediate environments compared to younger adults, leading to greater cumulative exposure to local hazards. Age-related mobility limitations further intensify their dependence on the neighborhood for meeting daily needs and accessing social support (Aneshensel et al., 2016). Empirical evidence also suggests a strong link between neighborhood physical environments and late-life physiological dysregulation and related health outcomes (Carbone, 2020a; Wang et al., 2022). Thus, exploring the influence of neighborhood risk factors would be particularly meaningful for them, as neighborhoods directly shape exposure to environmental stressors, which have significant implications for health and well-being in old age.

Among various neighborhood risk factors, neighborhood physical disorder (Sampson & Raudenbush, 2004), characterized by visible environmental stressors like broken windows, littered streets, and vacant buildings, has emerged as an environmental stressor linked to biomarkers and age-related health decline (Qin et al., 2025; Ross & Mirowsky, 2001). Growing evidence suggests that older adults in disordered neighborhoods exhibit elevated levels of biomarkers indicative of metabolic and inflammatory dysfunction. These biomarkers serve as key mediators linking environmental stressors to cardiovascular diseases (Roberts et al., 2021; Selvin et al., 2010), diabetes (Black, 2003), and elevated morbidity and mortality (Emerging Risk Factors Collaboration et al., 2010). For instance, neighborhood problems, including neighborhood trash or litter, noise, etc., are significantly linked to inflammatory markers, such as CRP and IL-6, which are key indicators of systemic inflammation and cardiovascular risk (Nazmi et al., 2010; Qin et al., 2025). Living in neighborhoods with physical disorder is associated with a higher body mass index (BMI), increased waist circumference, and elevated hemoglobin A1C (HbA1c), all of which are predictors of diabetes and metabolic dysfunction (Burdette & Hill, 2008; Chirinos et al., 2019). Collectively, these biomarkers may reflect distinct yet interrelated pathways through which neighborhood physical disorder elevates the biological risk of aging (Lavigne et al., 2021).

While previous studies have linked neighborhood stressors to metabolic and inflammatory biomarkers, most research relies on cross-sectional designs, leaving examinations of heterogeneous patterns in disorder trajectories largely understudied. Furthermore, residential selection bias, that is, individuals self-selecting into certain environments based on personal, socioeconomic, or health-related factors, is rarely addressed methodologically. Our study aims to bridge these gaps by (1) employing latent class analysis to identify distinct neighborhood physical disorder trajectory patterns over six years and (2) applying a machine learning based inverse probability weighting regression approach to account for residential selection. By characterizing trajectory patterns over time, our study provides new insights into the pathways through which residential environments shape inflammatory and metabolic risk in aging populations.

Several mechanisms may link neighborhood physical disorder with biological risk of aging. The social disorganization theory offers a theoretical framework for understanding the relationship between neighborhood conditions and biological risk among older adults. This theory posits that neighborhood structural factors, such as crime and physical disorder, can undermine collective efficacy, leading to fear of victimization and subsequent social withdrawal among residents (Cagney et al., 2009). Within these structurally disadvantaged communities, the capacity to regulate individual behaviors is weakened, leading to visible signs of physical and social decay, such as vacant buildings, graffiti, and litter (Ross & Mirowsky, 2001). As a manifestation of social disorganization, neighborhood physical disorder not only engenders environments where residents experience vigilance and fear but also generates chronic stressors that exacerbate vulnerability in older adults. This is supported by empirical evidence that residents in disordered neighborhoods report greater exposure to and intensity of daily stressors and safety concerns (Qin et al., 2025).

While the social disorganization theory explains the structural origins of neighborhood stressors, the stress process theory further maps these stressors into health consequences (Pearlin, 1989). The stress process theory conceptualizes stress as a dynamic process where external, environmental, or psychosocial demands overwhelm an individual's adaptive capacity, resulting in the accumulation of physiological and psychological strain that can jeopardize health (Thoits, 2006). This framework informs our understanding of how repeated exposure to stressors in disordered environments can erode resilience over time, resulting in sustained activation of stress responses that dysregulate physiological systems, accelerate biological aging, and increase disease vulnerability (Choi & Ailshire, 2024).

The mechanism linking neighborhood physical disorder to health risks may be partly rooted in the body’s stress response (Burdette & Hill, 2008). Chronic exposure to neighborhood physical disorder can trigger heightened vigilance and sustained stress responses. Physiological and psychological stress activates the hypothalamic-pituitary-adrenal (HPA) axis and the sympathetic nervous system (SNS), leading to the release of pro-inflammatory cytokines like interleukin-6 (IL-6) and high-sensitivity C-reactive protein (hsCRP) (Black, 2003; Qin et al., 2025). Chronic stress and the resulting low-grade inflammation accelerate the aging processes of various organs (e.g., the cardiovascular system). These exposures induce harmful biological responses, contributing to premature organ aging and an increased risk of metabolic dysregulation, manifesting in elevated hemoglobin A1c (HbA1c), metabolic abnormalities, and anthropometric changes (Carbone, 2020a; Chirinos et al., 2019; Murray et al., 2010). For example, Lavigne (2021) found that residents in disordered neighborhoods exhibit 2% higher levels of HbA1C, 13% higher levels of hsCRP, and 10% higher levels of IL-6, compared to those with no exposure. Epigenetic research further reveals that neighborhood physical disorder is associated with accelerated epigenetic aging (Choi & Ailshire, 2024), which further elucidates the biological toll of exposure to environmental stressors among older residents (Buschmann et al., 2018).

Despite the well-documented associations between neighborhood physical disorder and metabolic and inflammatory risk, much of the existing research relies on cross-sectional data, providing only a snapshot of physical disorder at a single point in time. This cross-sectional approach not only fails to account for cumulative exposure to neighborhood physical disorder but also aggravates concerns about reverse causation (Gustafsson et al., 2014). Recent review articles suggest that prolonged exposure, often spanning several years, is typically required for the effects of neighborhood risks on health to become evident (Jivraj et al., 2019; Oakes et al., 2015). This emphasizes the need for a longitudinal design to better understand the extent to which neighborhood environments are linked to health and well-being. In light of this gap, our study shifts the focus from static measurements of neighborhood physical disorder to a more dynamic perspective, considering both the duration and trajectory of exposure. We aim to identify distinct trajectory patterns based on changing exposures to neighborhood physical disorder among older individuals.

Residential mobility is selective, and neighborhoods also change over time (Osypuk & Acevedo-Garcia, 2010). Individuals are often non-randomly sorted into neighborhoods based on socioeconomic status, health conditions, or other individual-level characteristics. This sorting process may lead to spurious associations between neighborhood characteristics and health outcomes (Jivraj et al., 2019). To address this issue, recent research has employed inverse probability weighting (IPW) adjustments to account for selection into neighborhoods and disentangle neighborhood effects from confounding effects (Glymour et al., 2010). Standard IPW estimation typically employs logistic regression, which assumes linear and additive relationships between exposure and confounders. In practice, when these relationships are complex and nonlinear, model misspecification can bias weight estimates. To address this limitation, we leverage recent machine learning models for IPW estimation. These machine learning based algorithms, such as the Super Learner and generalized boosted regression trees (GBRT), are flexible in modeling linear, nonlinear (e.g., quadratic, logistic), and interactive relationships without requiring predefined functional forms, thereby improving the efficiency and accuracy of estimations (Yu et al., 2022). In this study, we rigorously assessed multiple machine learning based IPW algorithms and then selected the optimal model to mitigate selective confounding when estimating the associations of neighborhood physical disorder trajectories on aging-related biological risk.

Using a nationally representative longitudinal sample of U.S. older adults from the National Health and Aging Trends Study (NHATS, 2011–2017), this study investigates associations between neighborhood physical disorder trajectories and metabolic and inflammatory biomarkers. Current studies linking neighborhood physical disorder to biomarkers remain limited. Most evidence highlights the importance of perceived neighborhood disorder as subjective appraisals of visible decay, which provides valuable insight into the psychosocial pathways through which neighborhood conditions may influence biological aging (Carbone, 2020b, 2020a; Chirinos et al., 2019; Qin et al., 2025). Building on this work, our study utilizes interviewer-assessed measures of neighborhood physical disorder available in the NHATS dataset to mitigate potential perception bias and facilitate comparisons across individuals. Specifically, we aim to answer two research questions: (1) What are the patterns of neighborhood physical disorder experienced by these older adults over the study period? (2) What are the relationships between exposure to different patterns of neighborhood physical disorder and metabolic and inflammatory biomarkers for this population-based cohort of older adults? Given the established relationship between adverse neighborhood conditions and disease risks, we hypothesize that living in neighborhoods with higher physical disorder is associated with metabolic syndrome and inflammation, as indicated by elevated levels of metabolic and inflammatory biomarkers.

2. Research Design and Methods

2.1 Data and Sample

The National Health and Aging Trends Study (NHATS) is a nationally representative longitudinal cohort study of Medicare beneficiaries aged 65 years and older. Respondents were recruited from the Medicare enrollment database using a stratified three-stage sample design and have been followed annually since 2011, with a replenished cohort introduced in 2015. Detailed information about the NHATS study design and procedures has been published elsewhere (Freedman & Kasper, 2019). For this study, we utilized respondents' information from Round 1

(2011) to Round 7 (2017). Key sociodemographic information, such as race/ethnicity, gender, and education, was obtained at baseline (2011). Neighborhood physical disorder was included as repeated measures from Round 1 to Round 6. Blood biomarkers and anthropometric markers were collected in 2017 (Round 7). All respondents who completed the 2017 interview were invited to participate in a dried blood spot (DBS) collection, except those whose interviews were conducted by proxies. Among the eligible respondents (n = 5,266), 4,648 (88%) successfully provided a blood specimen. We excluded nursing home respondents (n = 37), as neighborhood characteristics were less relevant to them. We also excluded the replenished cohort to ensure all respondents had an equal length of neighborhood measures (n = 2,274). After further excluding those with missing data in biomarkers and baseline covariates (n = 53), our final analytic sample included 2,284 community-dwelling older adults. Supplementary Figure S1 shows the sample selection process.

2.2 Measures

Metabolic and inflammatory biomarkers. We included five biomarkers from the Round 7 DBS survey reflecting metabolism and inflammation. They were hemoglobin A1c (HbA1c) in %, body mass index (BMI), waist circumference in cm, high-sensitivity CRP (hsCRP) in mg/L, and interleukin-6 (IL-6) in pg/mL. HbA1c, hsCRP, and IL-6 were assayed based on the dried blood spot. Detailed assay procedures are described elsewhere (Kasper et al., 2019). Assay results were available as direct analyte concentrations or plasma-equivalent concentrations. We used plasma-equivalent values to facilitate clinical interpretation and comparison with other published metrics (Lavigne et al., 2021). The distributions of all biomarkers were skewed; thus, log transformations were applied prior to the analysis.

Neighborhood physical disorder. Using data from Round 1 through Round 6, neighborhood physical disorder was assessed with a 3-item environmental checklist completed by the NHATS interviewers based on their observations of the residential environments around the respondents' residences (Cagney et al., 2009). Interviewers documented the extent to which they observed the following when standing in front of respondents' homes or buildings: 1) litter or trash on the ground; 2) graffiti on walls; and 3) vacant homes or stores. Responses were recorded on a 4-point scale: none (1), a little (2), some (3), and a lot (4). A total score was calculated for each survey round by summing these items, with higher scores indicating greater physical disorder (Cronbach's α ranged from 0.82 to 0.98). Due to the highly skewed distributions of these measures and the very low prevalence of disorder (only around 10% for each survey round), we dichotomized this scale to indicate no physical disorder (0) and the presence of any physical disorder (1) for each survey round.

Covariates. We included a rich array of demographic information, early-life characteristics, health behaviors, geographic factors, and housing information. These covariates included gender (male or female), race/ethnicity (White, Black, Hispanic, or Other), age groups (65–69, 70–74, 75–79, 80–84, 85–89, or 90 and older), educational attainment (less than high school, high school graduate or GED, some college but no degree, or college degree or above), nativity status (whether born in the United States), childhood financial status (poor, average, or good), marital status (separated/divorced/widowed/never married or married/partnered), ever smoked (no or yes), experiencing financial strain (defined as any of the following: lack of money for 1) rent/mortgage, 2) utility bills, or 3) medical/prescription bills in the past month, or 4) skipping meals in the past month), homeownership (rented or not rented), urbanicity (whether one resided in a metropolitan area), and U.S. region based on the Census classification (Northeast, Midwest, South, or West).

All covariates were measured at baseline. Since health conditions likely lie on the pathway between neighborhood physical disorder and biological risks, health variables were not controlled for in these analyses (Samuel et al., 2022).

2.3 Analytic Strategies

We conducted latent class analysis (LCA) to identify neighborhood physical disorder trajectory patterns using data from Round 1 to Round 6. LCA is a finite mixture model that assumes a finite number of unobserved subgroups, or latent classes, within a population based on observed categorical data. Utilizing maximum likelihood estimation, individuals are assigned to distinct latent classes according to their estimated posterior membership probabilities. This method is particularly useful for uncovering underlying structures and identifying heterogeneous subgroups within a population. In this study, we first conducted multiple imputation for respondents who had missing values in neighborhood physical disorder measures. Then, we tested two- to five-latent class solutions to determine the most parsimonious and statistically meaningful classification of neighborhood physical disorder trajectories. The optimal number of groups was determined based on model fit indices including the Bayesian Information Criterion (BIC) and the g-squared likelihood ratio chi-square test, combined with a graphical examination to assess whether a certain number of latent patterns provided a clearer theoretical interpretation of the data. Once the best model was selected, respondents were classified into subgroups according to their posterior membership probabilities. We then performed a bivariate analysis to cross-tabulate trajectory subgroups with respondents' baseline characteristics.

Next, we conducted regression analyses to assess the association between the identified neighborhood physical disorder trajectory subgroups and biomarkers. Observational studies examining neighborhood effects on health outcomes may be biased owing to differences in individual characteristics correlated with both neighborhood exposure and health outcomes or the lack of an equivalent control group. For example, individuals exposed to long-term neighborhood physical disorder may systematically differ from those unexposed in terms of their socioeconomic status and health behaviors. To address this issue, we employed machine learning based inverse probability weighted (IPW) regression. This approach allows us to mimic a quasi-experimental design while accounting for differential probabilities of exposure to various patterns of neighborhood physical disorder.

Specifically, the regression analysis proceeded in two steps. First, three machine learning-based algorithms were estimated to generate the propensity score by including a comprehensive set of baseline covariates, including age, gender, race/ethnicity, education, marital status, nativity status, childhood financial status, ever smoking, current financial strain, home ownership, urbanicity, and residential region (Lavigne et al., 2021). These three algorithms were Generalized Boosted Modeling (GBM) (McCaffrey et al., 2004), Bayesian Additive Regression Trees (BART) (Chipman et al., 2010), and the Super Learner algorithm. Both GBM and BART are tree-based ensemble methods that utilize decision trees for weight estimation. Super Learner is an ensemble approach that optimally combines predictions from multiple base learners (models) to achieve improved predictive performance (Laan et al., 2007). In our analysis, the Super Learner included Lasso regression, XGBoost, and Random Forest as base learners. Among these three machine learning approaches, the algorithm that balanced all covariates was selected as the optimal algorithm to generate IPWs (Chen & Mallory, 2021). Covariate balance was considered achieved if the standardized mean difference was less than 0.1. IPWs were then calculated with the inverse of the propensity scores and were truncated at the 95th percentile to account for extreme values

(Austin & Stuart, 2015). Final analytic weights were created by multiplying the IPWs by the NHATS survey weights, which accounted for the complex study design (i.e., stratum and cluster), attrition, and non-response. Second, we performed weighted ordinary least squares regression analyses, using each of the biomarkers as the outcome and the identified neighborhood physical disorder trajectory subgroups as the predictor. Statistical tests were two-sided, with a significance level of $p < 0.05$. Data analyses were performed using RStudio version 4.0.2 (R Core Team, 2021), R package WeightIt (Greifer, 2023), and STATA 17 (StataCorp, 2021).

We conducted several sensitivity analyses. First, to validate the latent class trajectory group classification, we performed a group-based trajectory model and tested the agreement between the group membership from these two modeling strategies. Second, we repeated the analyses of HbA1c among respondents who reported a diagnosed diabetes to test whether the observed associations persisted within this clinical subgroup. Third, we dichotomized hsCRP values using a clinical cutoff of >3 mg/L to define high risk (Ridker, 2003) and estimated a logistic regression model to examine the consistency of our findings. Finally, we tested alternative weight truncation at the 90th and 99th percentiles in the regression analyses to assess the robustness of our results.

3. Results

Descriptive statistics of the sample at baseline are presented in Table 1. The final analytical sample included 2,284 community-dwelling older adults, representing an estimated 10,599,695 U.S. older adults. In the weighted sample, 57.2% of the respondents were female, 81.1% were non-Hispanic White, 8.2% were non-Hispanic Black, 6.9% were Hispanic, and other racial and ethnic groups accounted for 3.9%. Only 18.7% of the respondents had an education level lower than high school. Most of them were not smoking (93.8%). Eighty-two percent (81.7%) of these older adults lived in metropolitan areas. Approximately 5.6% reported currently experiencing financial strain.

Table 1 about here

To identify trajectory patterns of neighborhood physical disorder, we performed latent class analyses and tested two- to five-group solutions. Model fit indices indicated that a four-class solution (BIC = 10485.29) yielded the best model fit (Supplementary Table S1). From this model, four distinct subgroups were identified (Figure 1). The majority of individuals in this sample experienced stable low neighborhood physical disorder (1,929, 84.5%). In contrast, a small number of respondents had stable high exposure to neighborhood physical disorder (66, 2.9%). The remaining groups were characterized by either increased exposure (74, 3.2%) or decreased exposure (215, 9.4%) over time.

Figure 1 about here

Table 2 presents the characteristics of respondents across four trajectory subgroups. Older adults with stable exposure to high levels of physical disorder were more likely than those in other groups to be non-Hispanic Black (59.1%) or Hispanic (12.1%), unmarried (65.2%), current smokers (22.7%), have less than a high school education (51.5%), experience financial strain (19.7%), and rent their homes (22.7%). In contrast, the stable low exposure group was the most socioeconomically advantaged. They were predominantly non-Hispanic White (81.6%), highly educated (college educated: 32.1%), financially secure (95.1%), and homeowners (90.0%). Respondents with decreased exposure shared similar characteristics with the increased exposure group, including low education levels and economic insecurity, although to a slightly lesser extent. We further examined bivariate associations between the four subgroups and biomarkers (Supplementary Figure S2). Significant group differences were found in HbA1c and hsCRP. Older adults who were exposed to stable high disorder showed the highest levels of HbA1c and hsCRP, followed by those with increased exposure, compared to the other two groups.

Table 2 about here

Prior to the regression analyses, we evaluated the performance of three machine learning algorithms for IPW estimation (Figure 2 and Supplementary Table S2). We found that GBM exhibited the best performance compared to BART and Super Learner, as it achieved full covariate balance across all variables. In contrast, BART balanced 80% (n = 18) of covariates, and Super Learner balanced 70% (n = 16) of covariates. Supplementary Figure S3 further confirmed that GBM-derived IPWs successfully balanced all covariates (standardized differences > 0.1). Based on these results, we selected GBM to generate IPWs for subsequent weighted regression analyses.

Figure 2 about here

Findings from IPW-adjusted regression models are presented in Figure 3 and Supplementary Table S3. Older adults with increased exposure (b = 0.04, 95% CI: 0.01-0.08), decreased exposure (b = 0.02, 95% CI: 0.01-0.05), and stable high exposure (b = 0.10, 95% CI: 0.03-0.17) to neighborhood physical disorder showed significantly higher levels of HbA1c compared to those with stable low exposure. We did not find significant results for other metabolic biomarkers. In terms of inflammatory biomarkers, older adults living in neighborhoods with stable high disorder had significantly higher levels of hsCRP (b = 0.25, 95% CI: 0.05-0.45) compared to their counterparts with stable low exposure. There was no significant association between neighborhood physical disorder trajectories and IL-6.

Figure 3 about here

In the sensitivity analyses, we found substantial agreement between our current group classification and the results obtained from group-based trajectory models (κ = 0.6). This indicates that our LCA results were robust under various models and data setups (Supplementary Figure S4). Subgroup analysis from respondents with diabetes revealed a significant positive association between stable high exposure and HbA1c levels, whereas associations for the increased and decreased exposure groups were not statistically significant (Supplementary Table S4). These findings may partly reflect limited statistical power, as only 634 (28 %) respondents reported a diabetes diagnosis. Results from the dichotomized hsCRP model yielded similar findings (Supplementary Table S5). Inferences remained unchanged in sensitivity analyses using alternative weight truncation (results are available upon request).

4. Discussion

In response to the aging society, there has been a growing interest in exploring environmental factors that enable healthy aging in place (WHO, 2023). This study informs such efforts by examining the association between neighborhood physical disorder trajectory patterns and metabolic and inflammatory biomarkers among a nationally representative sample of U.S. older adults. While prior research has linked neighborhood physical disorder to biomarkers, existing studies are either cross-sectional or fail to account for heterogeneous patterns. By characterizing trajectories of neighborhood physical disorder, our study captures the dynamic changes that cross-sectional measures are unable to capture. We also advance the literature by implementing machine learning based inverse probability weighting to address residential selection. These machine learning algorithms are flexible in capturing complex, non-linear relationships in high-dimensional covariate data. Our findings underscore important practical considerations when applying these algorithms. While different machine learning methods offer distinct theoretical advantages, their performance varies substantially in practice. Thus, evaluating multiple algorithms and relying on diagnostic statistics are essential for guiding algorithm selection.

We identified four subgroups representing various trajectories of stability and changes in neighborhood contexts. Results from the LCA revealed that approximately 85% of respondents lived in neighborhoods characterized by stable low physical disorder, while a small portion (3%) experienced stable exposure to high disorder. These patterns suggest that most older adults experienced stable neighborhood contexts over time. This finding is consistent with previous research showing little or no change in neighborhood conditions among community-dwelling older people (Gill et al., 2025; Jivraj et al., 2019). We also identified that only 20% of the respondents changed their residential address during the study period, suggesting the likelihood that neighborhood risks may accumulate over time, especially for older residents. Notably, racial and ethnic minority groups, individuals with lower education, and those with financial strains were disproportionately represented in the stable high exposure group. This may indicate persistent residential stratification along racial, ethnic, and socioeconomic lines (Acevedo-Garcia et al., 2003; Osypuk & Acevedo-Garcia, 2010).

Our research revealed pronounced associations between various trajectory patterns of neighborhood physical disorder and HbA1c. These associations remained statistically significant after accounting for individual-level characteristics that may influence both physical disorder exposure and biomarker outcomes. However, some clinical and observational studies have reported weak or nonsignificant associations. For example, Gary et al. (2008) found no significant relationship between neighborhood problems and HbA1c in a cross-sectional analysis. These discrepancies may be attributed to variations in study design, sample size, and measurement strategies. Whereas earlier studies often relied on cross-sectional designs, regional samples, or participants' subjective reports of neighborhood conditions, our study leveraged a nationally representative cohort and used standardized observer assessments of physical disorder. Our results aligned with previous studies showing a negative association between neighborhood physical disorder and HbA1c in the NHATS sample (Lavigne et al., 2021). Notably, the consistent relationships of HbA1c with multiple exposure patterns suggest this biomarker may be particularly sensitive to the physiological imprint of neighborhood physical disorder. Thus, HbA1c could serve as a valuable biomarker for assessing the potential long-term consequences of residing in disadvantaged neighborhoods on metabolic health.

While neighborhood physical disorder is associated with HbA1c, the associations with anthropometric measures, such as BMI and waist circumference are not significant. Although a systematic review confirmed a link between neighborhood socioeconomic status and BMI in the general population (Mohammed et al., 2019), evidence regarding neighborhood physical disorder trajectories and BMI remains scarce. Among the few longitudinal investigations, Letarte and colleagues (2022) found that females residing in neighborhoods characterized by deprived upward, deprived downward, and stable deprived trajectories had significantly higher obesity risks compared to those in the stable low deprived trajectory. Moreover, substantial heterogeneities also exist in neighborhood effects on weight status. For instance, using a probability sample from Texas, Chirinos and colleagues (2019) found significant associations between neighborhood physical disorder and BMI across racial/ethnic groups. However, Keita et al. (2014) reported that living in a deprived neighborhood was associated with a higher BMI and a larger waist circumference among White middle-aged and older adults, but not among their Black counterparts. Some research also suggests stronger neighborhood effects on women than on men (Robert & Reither, 2004). Due to the small sample size in the stable high exposure group, we were not able to conduct analyses examining gender or racial/ethnic differences. Future studies are needed to examine the mechanisms underlying the heterogeneity of neighborhood effects across social-demographic groups.

In terms of inflammatory biomarkers, our findings indicate that only persistent exposure to high neighborhood physical disorder is significantly associated with elevated subsequent levels of hsCRP. We observed nonsignificant associations between neighborhood physical disorder and IL-6. Empirical evidence suggests that the inflammatory response is a crucial biological pathway linking neighborhood disorder to negative health outcomes (Qin et al., 2025; Roberts et al., 2021). Our findings further illustrate that hsCRP is particularly responsive to consistent exposure to environmental stressors like neighborhood physical disorder. The heightened susceptibility of hsCRP to chronic stress may be partially attributed to the increased frequency of daily stressors (e.g., graffiti, litter) experienced by older residents (Qin et al., 2025). Notably, older adults are more vulnerable than younger adults due to age-related immunosenescence (Santoro et al., 2021). Their weakened immune systems become less capable of resolving inflammation, creating a biological feedback loop that amplifies tissue damage and metabolic dysfunction. Therefore, the accumulation of stable, high levels of neighborhood physical disorder may "get under the skin" and pose a uniquely pronounced health risk for older residents. Given that CRP is an independent predictor of cardiometabolic risk (Ridker, 2003), identifying individuals with clinically high-risk hsCRP and their neighborhood environments could enhance clinical risk stratification and help older adults who may benefit most from targeted inflammation screening and cardiometabolic preventive strategies.

Our findings have important implications. In clinical settings, healthcare practitioners should consider screening patients for stressors related to environmental risks and neighborhood hazards. Identifying patients living in high-disorder neighborhoods can help clinicians recognize those at greater risk for various health conditions. While our study highlights the association between neighborhood physical disorder and the biological risk of aging, recent randomized controlled trials provide causal evidence supporting the positive influence of neighborhood interventions on health outcomes. For instance, a citywide cluster randomized controlled trial in Philadelphia demonstrated that greening vacant lots significantly reduced stress and improved mental health among residents (South et al., 2018). This evidence underscores that addressing neighborhood physical disorder can be effective through community-level interventions. Policy efforts focusing on investing in safer streets, green spaces, and recreational facilities can promote physical activity and reduce stress (Carpenter, 2013). To better address issues like littering and graffiti, policies could involve increasing community-based cleanup initiatives, installing more public trash receptacles, and creating designated spaces for street art to reduce environmental risks and promote healthy aging in place (WHO, 2023).

There are several limitations of this study. First, the measurement of neighborhood physical disorder in the NHATS survey includes only three items, which may not capture other important forms of neighborhood physical disorder, such as noise, which can disrupt sleep and act as a chronic stressor. It is possible that the prevalence of neighborhood physical disorder was underestimated in this sample. Second, the small sample sizes of the LCA subgroups—particularly those living in neighborhoods with increased exposure, decreased exposure, and stable high exposure — may limit the statistical power of the analysis, which could lead to an underestimation of the effects. Further studies with larger longitudinal samples are required to better validate the results from those with differential patterns of exposure. Third, we dichotomized the disorder scale because of its skewed, zero-inflated distribution. This may obscure meaningful variations in levels of physical disorder across neighborhoods. Fourth, both latent class analysis and machine learning techniques are data-driven methods. The “black box” nature of machine learning may reduce interpretability relative to traditional parametric models. When deciding between these algorithms, it is essential to evaluate a range of algorithms and rely on empirical diagnosis for model selection. Lastly, despite using IPW to adjust for confounders, residual confounding might persist, especially if unmeasured confounders influenced both neighborhood physical disorder and health outcomes. As such, our findings may not be interpreted as causal.

In conclusion, our findings reveal significant associations between long-term exposure to neighborhood physical disorder and metabolic and inflammatory biomarkers among older adults. Specifically, those with stable high exposure to neighborhood physical disorder exhibit higher levels of HbA1c and hsCRP compared to their counterparts with stable low exposure. These results underscore the critical role of proximal residential environments in influencing the biological risk of aging. Incorporating screenings for environmental determinants of health into routine healthcare visits for older adults could be a viable way to improve health outcomes and support healthy aging in place. Additionally, addressing neighborhood physical disorder through targeted policies and community initiatives can be pivotal in mitigating environmental health risks.

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Statements and Declarations

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. The IZA Discussion Paper Series serves as *a preprint server* to deposit latest research for early feedback. News media inquiries may be directed to Xi Chen xi.chen@yale.edu or Jiao Yu jiao.yu@yale.edu. We appreciate your interest.

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Table 1. Descriptive Statistics of Study Sample at Baseline

Variables	Unweighted	With survey weights
N	2,284	10,599,695
Female	1,343 (58.8%)	6,061,902 (57.2%)
Race		
Non-Hispanic White	1,706 (74.7%)	8,592,225 (81.1%)
Non-Hispanic Black	415 (18.2%)	866,317 (8.2%)
Hispanic	114 (5.0%)	732,581 (6.9%)
Other	49 (2.1%)	408,572 (3.9%)
Education		
Less than high school	453 (19.8%)	1,978,468 (18.7%)
High school	754 (33.0%)	3,528,276 (33.3%)
Some college	423 (18.5%)	1,952,306 (18.4%)
College and above	654 (28.6%)	3,140,645 (29.6%)
Age		
65 to 69	591 (25.9%)	3,601,682 (34.0%)
70 to 74	585 (25.6%)	2,788,403 (26.3%)
75 to 79	508 (22.2%)	2,036,291 (19.2%)
80+	600 (26.3%)	2,173,318 (20.5%)
Marital status		
Not married	992 (43.4%)	4,213,110 (39.7%)
Married or partnered	1,292 (56.6%)	6,386,586 (60.3%)
Current Smoking		
No	2,138 (93.6%)	9,945,137 (93.8%)
Yes	146 (6.4%)	654,558 (6.2%)
Rented home	272(11.9%)	1,212,867 (11.4%)
Childhood financial status		
Poor	847 (37.1%)	3,803,906 (35.9%)
Average	1,133 (49.6%)	5,321,867 (50.2%)
Good	304 (13.3%)	1,473,922 (13.9%)
Born in the US	2,089 (91.5%)	9,410,975 (88.8%)
Having finance strain	143 (6.3%)	594,710 (5.6%)
Living in metropolitan	1,801 (78.9%)	8,664,987 (81.7%)
Census region		
Northeast	332 (14.5%)	1,883,129 (17.8%)
Midwest	610 (26.7%)	2,461,904 (23.2%)
South	910 (39.8%)	3,941,290 (37.2%)
West	432 (18.9%)	2,313,372 (21.8%)
Biomarkers (median, IQR)		
BMI (kg/m^2)	27.6 (5.6)	27.7 (5.6)
Waist circumference (cm)	39.7 (5.8)	39.8 (5.9)
HbA1c (%)	6.0 (0.9)	5.9 (0.9)
IL-6 (pg/mL)	6.9 (11.9)	6.7 (11.4)
hsCRP (mg/L)	2.3 (3.0)	2.2 (2.9)

Note. Frequencies with percentages n (%) and median with interquartile range (IQR) are presented. BMI = body mass index; HbA1c = hemoglobin A1C; IL-6 = interleukin-6; hsCRP = high-sensitivity CRP.

Table 2. Baseline Sample Characteristics by Neighborhood Physical Disorder Trajectory Subgroups

Variables (n, %)	Stable low exposure	Increased exposure	Decreased exposure	Stable high exposure	p
n	1,929 (84.5%)	74 (3.2%)	215 (9.4%)	66 (2.9%)	
Female	1,131 (58.6%)	45 (60.8%)	130 (60.5%)	37 (56.1%)	0.90
Race					<0.001
Non-Hispanic	1,575 (81.6%)	21 (28.4%)	93 (43.3%)	17 (25.8%)	
Non-Hispanic	256 (13.3%)	32 (43.2%)	88 (40.9%)	39 (59.1%)	
Hispanic	62 (3.2%)	16 (21.6%)	28 (13.0%)	8 (12.1%)	
Other	36 (1.9%)	5 (6.8%)	6 (2.8%)	2 (3.0%)	
Education					<0.001
Less than high school	284 (14.7%)	33 (44.6%)	102 (47.4%)	34 (51.5%)	
High school	653 (33.9%)	24 (32.4%)	54 (25.1%)	23 (34.8%)	
Some college	373 (19.3%)	8 (10.8%)	33 (15.3%)	9 (13.6%)	
College and above	619 (32.1%)	9 (12.2%)	26 (12.1%)	0 (0.0%)	
Age					0.82
65 to 69	498 (25.8%)	18 (24.3%)	53 (24.7%)	22 (33.3%)	
70 to 74	484 (25.1%)	24 (32.4%)	62 (28.8%)	15 (22.7%)	
75 to 79	438 (22.7%)	12 (16.2%)	44 (20.5%)	14 (21.2%)	
80+	509 (26.4%)	20 (27.1%)	56 (26.0%)	15 (22.7%)	
Marital status					<0.001
Not Married	778 (40.3%)	44 (59.5%)	127 (59.1%)	43 (65.2%)	
Married or partnered	1,151 (59.7%)	30 (40.5%)	88 (40.9%)	23 (34.8%)	
Current Smoking					<0.001
No	1,828 (94.8%)	65 (87.8%)	194 (90.2%)	51 (77.3%)	
Yes	101 (5.2%)	9 (12.2%)	21 (9.8%)	15 (22.7%)	
Rented house					<0.001
No	1,737 (90.0%)	60 (81.1%)	164 (76.3%)	51 (77.3%)	
Yes	192 (10.0%)	14 (18.9%)	51 (23.7%)	15 (22.7%)	
Childhood financial status					0.028
Poor	685 (35.5%)	34 (45.9%)	98 (45.6%)	30 (45.5%)	
Average	982 (50.9%)	31 (41.9%)	94 (43.7%)	26 (39.4%)	
Good	262 (13.6%)	9 (12.2%)	23 (10.7%)	10 (15.2%)	
Born in the US					<0.001
No	142 (7.4%)	15 (20.3%)	31 (14.4%)	7 (10.6%)	
Yes	1,787 (92.6%)	59 (79.7%)	184 (85.6%)	59 (89.4%)	
Having finance strain					<0.001
No	1,834 (95.1%)	64 (86.5%)	190 (88.4%)	53 (80.3%)	
Yes	95 (4.9%)	10 (13.5%)	25 (11.6%)	13 (19.7%)	
Urbanicity					0.72
Metropolitan	1,524 (79.0%)	55 (74.3%)	168 (78.1%)	54 (81.8%)	
Non-metropolitan	405 (21.0%)	19 (25.7%)	47 (21.9%)	12 (18.2%)	
Census region					0.004
Northeast	284 (14.7%)	9 (12.2%)	27 (12.6%)	12 (18.2%)	
Midwest	523 (27.1%)	14 (18.9%)	57 (26.5%)	16 (24.2%)	
South	738 (38.3%)	44 (59.5%)	95 (44.2%)	33 (50.0%)	
West	384 (19.9%)	7 (9.5%)	36 (16.7%)	5 (7.6%)	

Note. Frequencies with percentages *n* (%) are presented. χ^2 tests were performed to compare group differences.

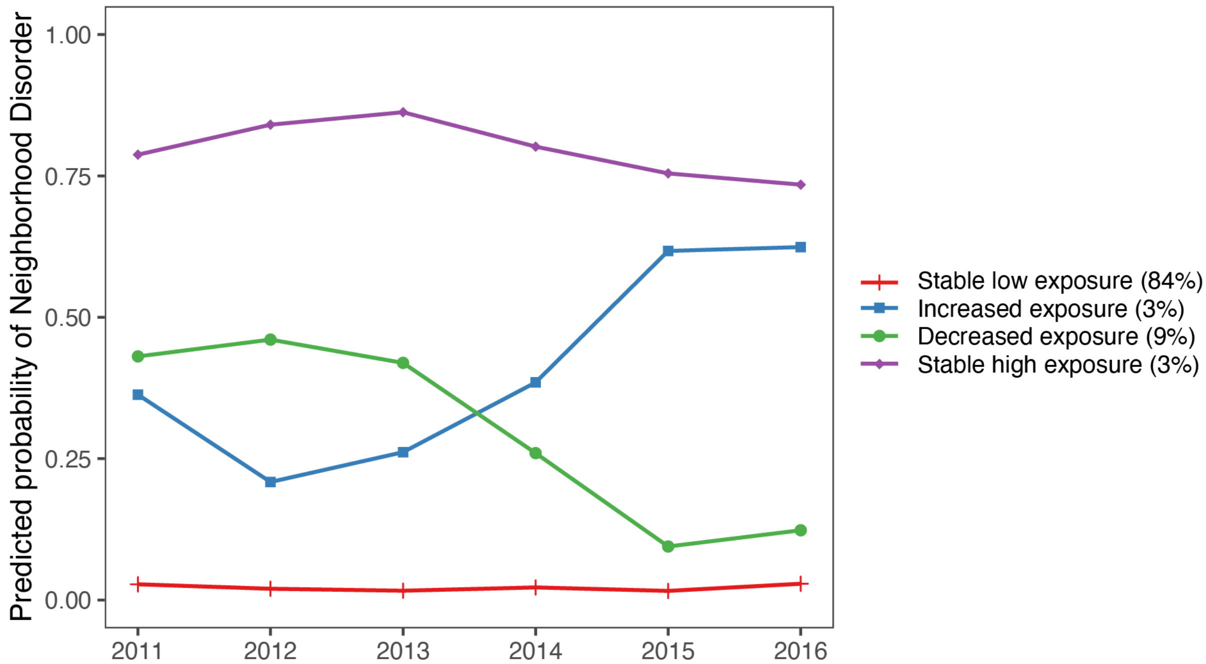


Figure 1. Predicted Probability of Exposure to Neighborhood Physical Disorder from Four Trajectory Subgroups Over Time (NHATS, 2011 - 2016)

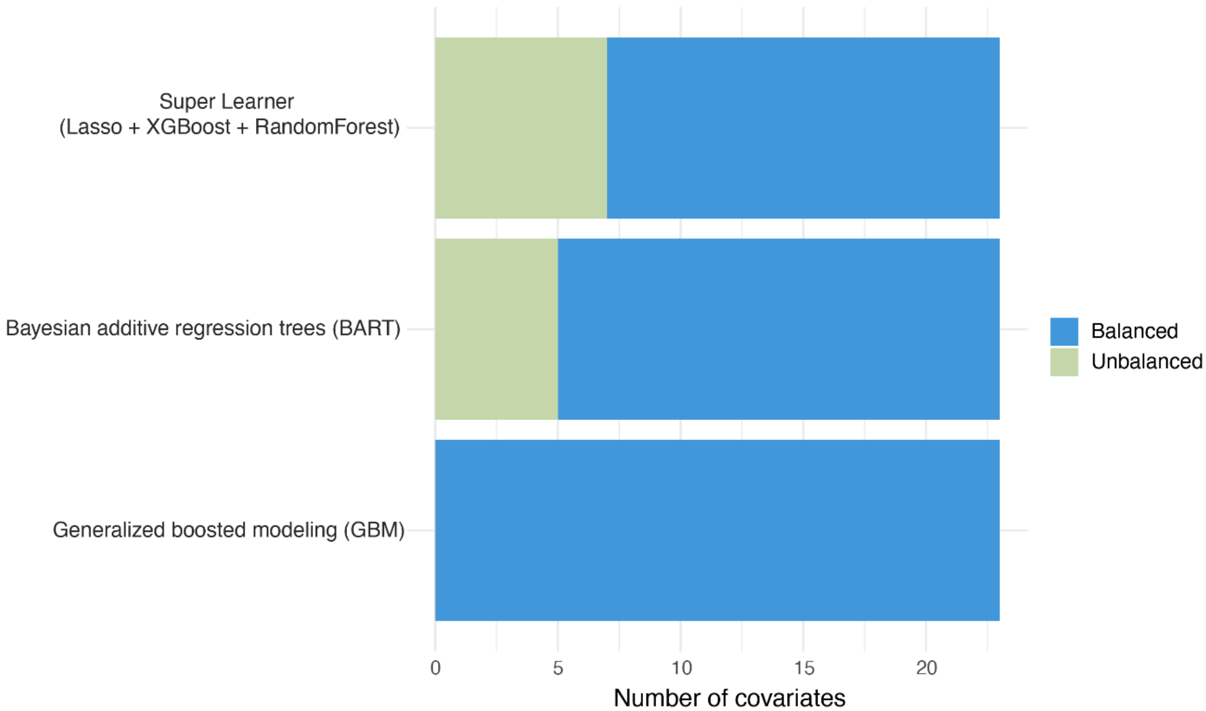


Figure 2. Covariate Balanced Plot of Three Machine Learning Based Inverse Probability Weighting Algorithms

Note: Covariate balance was achieved if the standardized mean difference was less than 0.1. The algorithm that balanced all covariates was selected as the optimal algorithm to generate inverse probability weights.

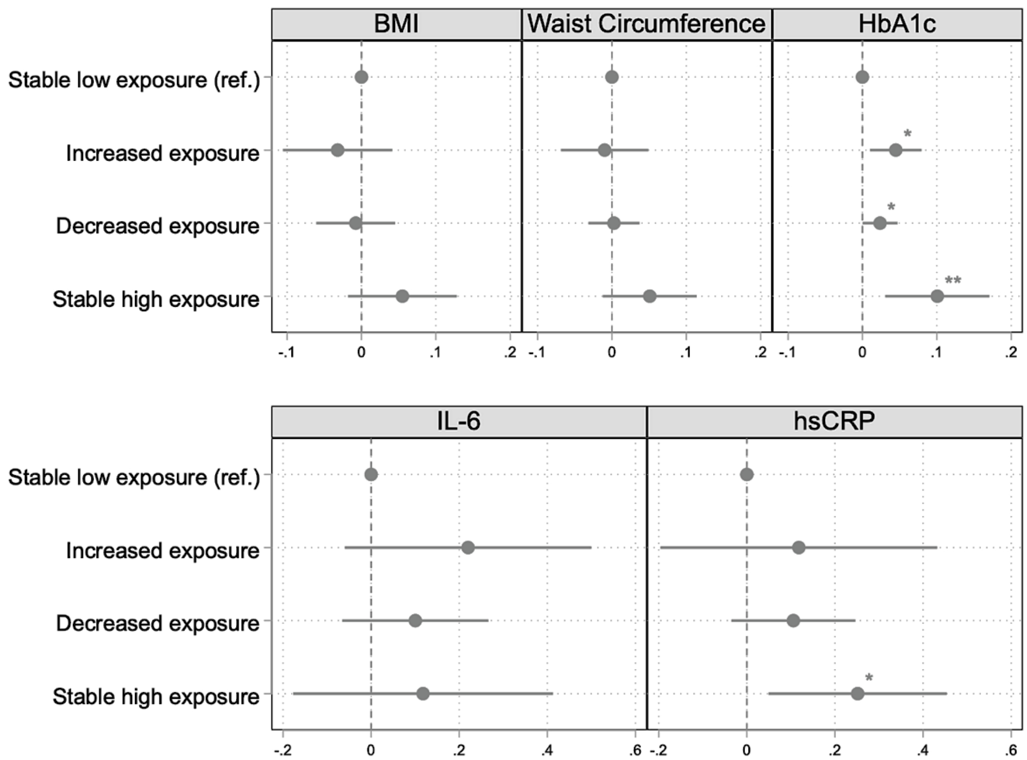


Figure 3. Regression Coefficients of Metabolic and Inflammatory Biomarkers (log transformed) and Neighborhood Physical Disorder Trajectory Subgroups (NHATS, 2011-2017)

Note: The stable low exposure group was the reference group. Inverse probability weights (derived from Generalized Boosted Modeling) were applied in regression models. Full model estimates are presented in Supplementary Table S3.
BMI = body mass index; HbA1c = hemoglobin A1C; IL-6 = interleukin-6; hsCRP = high-sensitivity C-reactive protein.
* p<0.05, ** p<0.01.

Supplementary Materials

- Supplementary Table S1. Latent Class Analysis Model Fit Statistics
- Supplementary Table S2. Comparison of Machine Learning Based Inverse Probability Weighting Algorithms
- Supplementary Table S3. Regression Coefficients of Metabolic and Inflammatory Biomarkers (log transformed) and Neighborhood Physical Disorder Trajectory Subgroups (NHATS, 2011-2017)
- Supplementary Table S4. Regression Coefficients of HbA1c and Neighborhood Physical Disorder Trajectory Subgroups among Respondents with Diabetes (NHATS, n = 634)
- Supplementary Table S5. Regression Coefficients of hsCRP and Neighborhood Physical Disorder Trajectory Subgroups (NHATS, 2011-2017)
- Supplementary Figure S1. Analytic Sample Selection Process
- Supplementary Figure S2. Bivariate Distribution of Metabolic and Inflammatory Biomarkers across Neighborhood Physical Disorder Trajectory Subgroups (Survey Weighted)
- Supplementary Figure S3. Covariates Balance Plot before and after Inverse Probability Weighting
- Supplementary Figure S4. Neighborhood Physical Disorder Trajectory Pattens Using Group-Based Trajectory Modeling

Supplementary Table S1. Latent Class Analysis Model Fit Statistics

	Log Likelihood	Degree of freedom	BIC
Class 2	-5190.227	13	10489.95
Class 3	-5159.636	20	10487.73
Class 4	-5128.939	27	10485.29
Class 5	-5117.957	34	10522.28

Note: BIC=Bayesian information criterion; BIC is used to assess goodness of fit with smaller values indicating better fit.

Supplementary Table S2. Comparison of Machine Learning Based Inverse Probability Weighting Algorithms

	Balance tally for target mean differences	
	# of covariates was balanced	# of covariates was unbalanced
Super Learner (combining Lasso, XGBoost, Random Forest)	16	7
Bayesian additive regression trees (BART)	18	5
Generalized boosted modeling (GBM)	23	0

Note: Covariate balance was achieved if the standardized mean difference was less than 0.1. The algorithm that balanced all covariates was selected as the optimal algorithm to generate IPWs

Supplementary Table S3. Regression Coefficients of Metabolic and Inflammatory Biomarkers (log transformed) and Neighborhood Physical Disorder Trajectory Subgroups (NHATS, 2011-2017)

	BMI	Waist Circumference	HbA1c	IL-6	hsCRP
	b [95% CI]	*b [95% CI]*	*b [95% CI]*	*b [95% CI]*	*b [95% CI]*
Increased exposure	-0.03	-0.01	0.04*	0.22	0.12
	[-0.11, 0.04]	[-0.07, 0.05]	[0.01, 0.08]	[-0.06, 0.50]	[-0.20, 0.43]
Decreased exposure	-0.01	0.003	0.02*	0.10	0.11
	[-0.06, 0.05]	[-0.03, 0.04]	[0.01, 0.05]	[-0.07, 0.27]	[-0.03, 0.25]
Stable high exposure	0.06	0.05	0.10**	0.12	0.25*
	[-0.02, 0.13]	[-0.01, 0.11]	[0.03, 0.17]	[-0.18, 0.41]	[0.05, 0.45]
Intercept	3.34***	3.70***	1.92***	1.74***	0.94***
	[3.33, 3.35]	[3.69, 3.71]	[1.92, 1.93]	[1.70, 1.78]	[0.90, 0.98]

Note: Coefficients and 95% confidence intervals were reported. Coefficients from IPW-adjusted ordinary least squares regression model estimations were reported. Biomarkers were log transformed.
The stable low exposure group was the reference group.
BMI: body mass index; HbA1c: hemoglobin A1C; IL-6: interleukin-6; hsCRP: High-sensitivity C-reactive protein.
** p<0.05, ** p<0.01, *** p<0.001.*

Supplementary Table S4. Regression Coefficients of HbA1c and Neighborhood Physical Disorder Trajectory Subgroups among Respondents with Diabetes (NHATS, n = 634)

	HbA1c
	b [95% CI]
Stable low exposure (reference)	
Increased exposure	0.03 [-0.02, 0.07]
Decreased exposure	0.003 [-0.03, 0.03]
Stable high exposure	0.05* [0.01, 0.10]
Intercept	2.03*** [2.02, 2.04]

Note: Coefficients and 95% confidence intervals were reported. Coefficients from an IPW-adjusted ordinary least squares regression model were reported. Biomarkers were log transformed.
HbA1c: hemoglobin A1C.
* *p<0.05,* ** *p<0.01,* *** *p<0.001.*

Supplementary Table S5. Regression Coefficients of hsCRP and Neighborhood Physical Disorder Trajectory Subgroups (NHATS, 2011-2017)

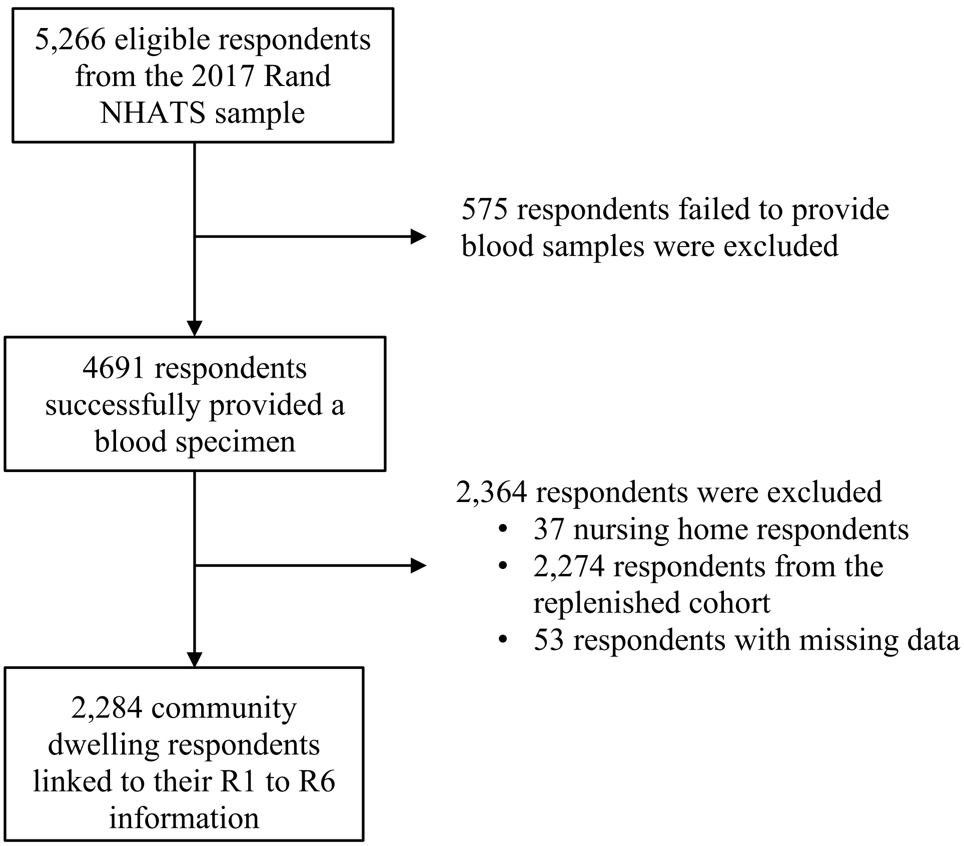
	hsCRP
	OR [95% CI]
Stable low exposure (reference)	
Increased exposure	1.27 [0.74, 2.20]
Decreased exposure	1.38 [0.99, 1.91]
Stable high exposure	2.03* [1.18, 3.51]
Intercept	0.27*** [0.24, 0.30]

Note: Odds ratio and 95% confidence intervals were reported. Coefficients from an IPW-adjusted logit regression model were reported. hsCRP were dichotomized at >3 mg/L.

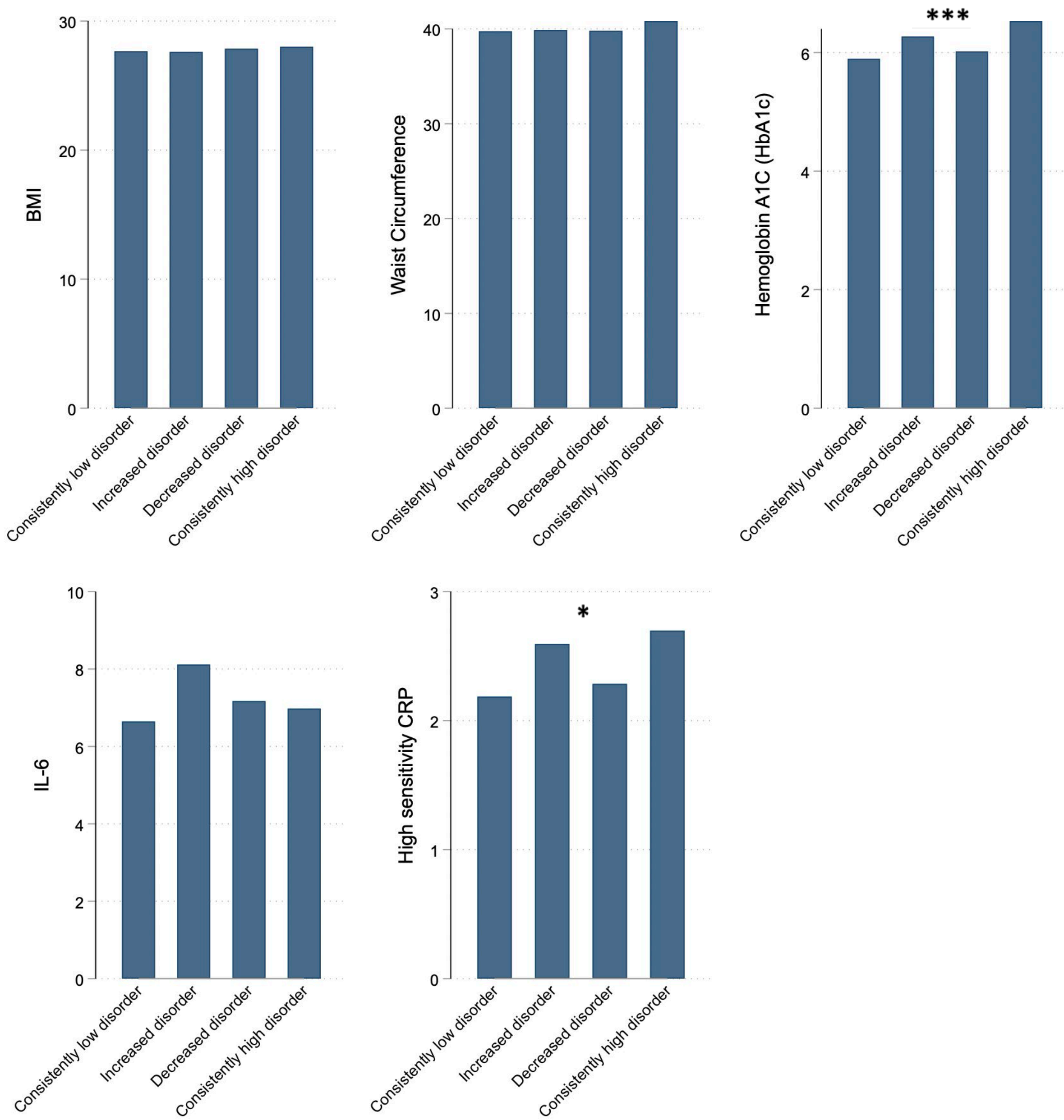
hsCRP: High-sensitivity C-reactive protein.

* *p<0.05, ** p<0.01, *** p<0.001.*

Supplementary Figure S1. Analytic Sample Selection Process



Supplementary Figure S2. Bivariate Distribution of Metabolic and Inflammatory Biomarkers across Neighborhood Physical Disorder Trajectory Subgroups (Survey Weighted)



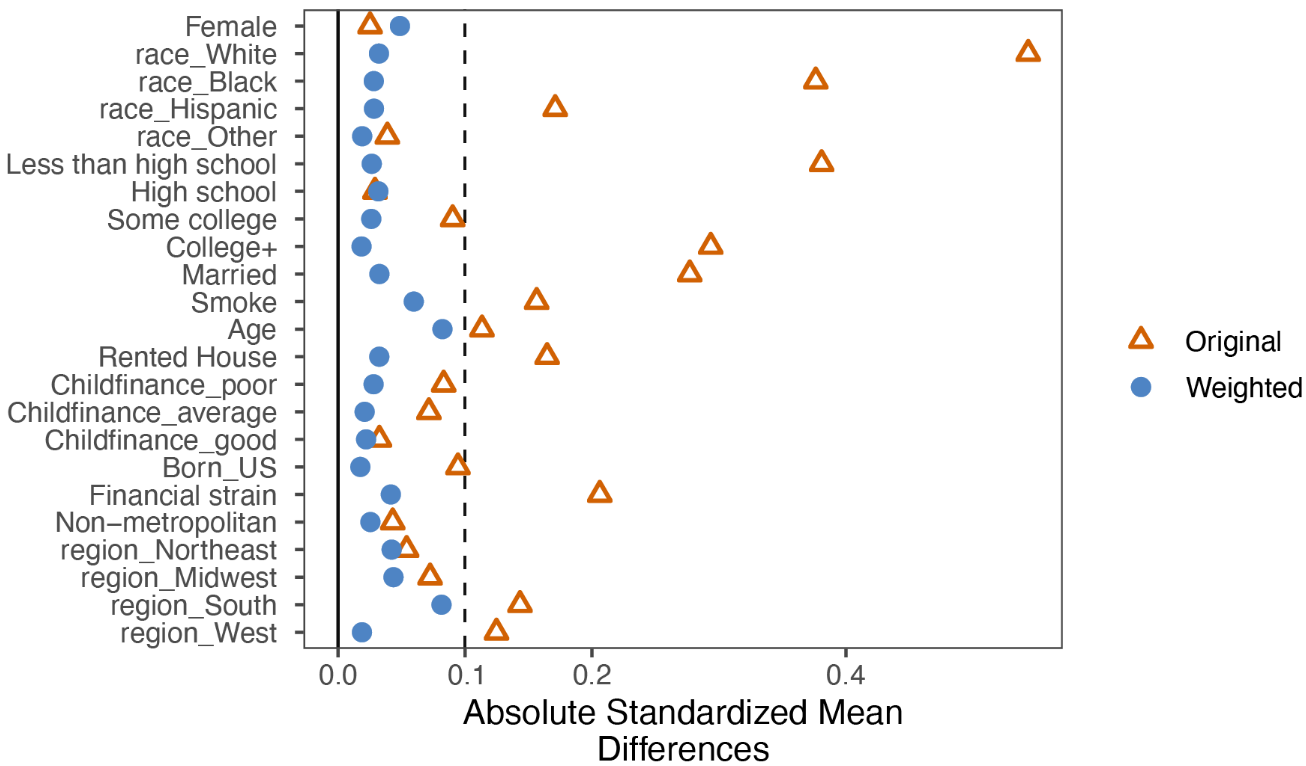
Note: Kruskal-Wallis rank sum tests were performed to compare statistical differences across groups.

BMI: body mass index; hsCRP: High-sensitivity C-reactive protein; IL-6: interleukin-6.

Survey weights were applied to allow inferences to be drawn to US older adult Medicare beneficiaries.

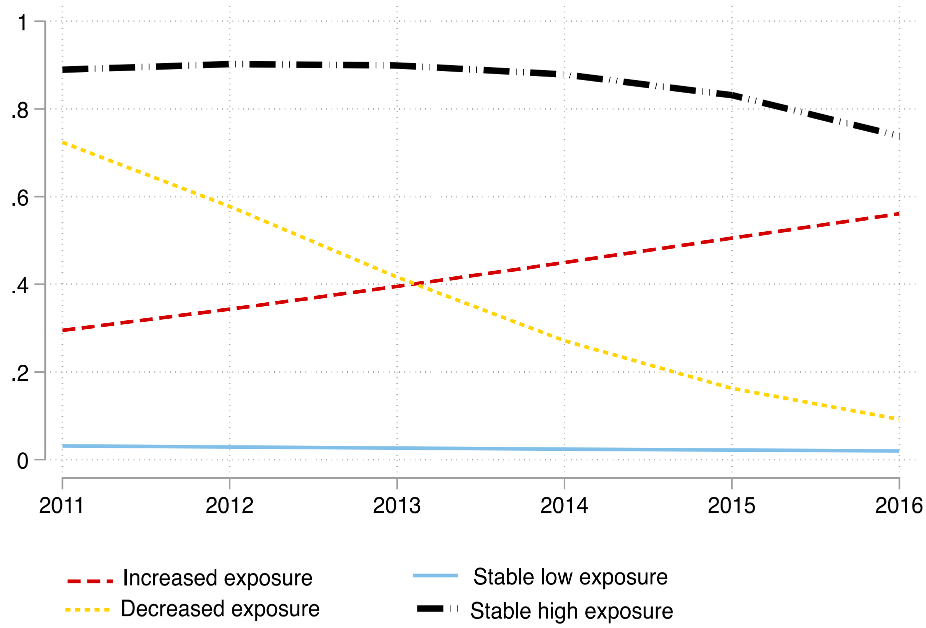
**p < .05, **p < .01, ***p < .001.*

Supplementary Figure S3. Covariates Balance Plot before and after Inverse Probability Weighting



Note: After applying IPWs, all covariates had a standardized difference of less than 0.1. All covariates were balanced after applying the GBM weighting adjustment.

Supplementary Figure S4. Neighborhood Physical Disorder Trajectory Pattens Using Group-Based Trajectory Modeling (GBTM, kappa= 0.6)



Note: Cohen's Kappa coefficient indicates the substantial agreement of GBTM grouping with the grouping presented in the main analysis (κ=0.6). Kappa coefficient ranges from -1 to 1, with higher values indicating higher agreement. Specifically, κ>0.6 indicate substantial agreement.