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Title: Mediating Role of Psychological Distress in the Associations between Neighborhood Social Environments and Sleep Health

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Abstract:

Study Objectives: Characteristics of neighborhood social environments, such as safety and social cohesion, have been examined as determinants of poor sleep. The current study investigates associations between neighborhood social characteristics and sleep health, as well as the mediating role of psychological distress on these possible associations.

Methods: Three waves of PHRESH Zzz (n=2,699), a longitudinal study conducted in two low-income, predominately Black neighborhoods, were utilized for this analysis. Characteristics of neighborhood social environments were measured using crime rates, a neighborhood social disorder index, and self-reported social cohesion. Sleep health was measured via 7 days of wrist-worn actigraphy as insufficient sleep, sleep duration, wake after sleep onset (WASO), and sleep efficiency. G-estimations based on structural nested mean models and mediation analyses were performed to estimate effects of neighborhood social environments on sleep as well as direct/indirect effects through psychological distress.

Results: Crime rate around residential addresses was associated with increased risk of insufficient sleep (risk ratio: 1.05 [1.02, 1.12]), increased WASO (β : 3.73 [0.26, 6.04]), and decreased sleep efficiency (β : -0.54 [-0.91, -0.09]). Perceived social cohesion was associated with decreased risk of insufficient sleep (OR: 0.93 [0.88, 0.97]). Psychological distress mediated part of the associations of crime and social cohesion with insufficient sleep.

Conclusions: Neighborhood social environments may contribute to poor sleep health in low-income, predominantly Black neighborhoods, and psychological distress can be a salient pathway linking these neighborhood characteristics and sleep health.

Keywords: neighborhood, crime, social cohesion, neighborhood disorder, sleep, actigraphy, psychological distress, mediation analysis

Statement of Significance: The majority of studies on neighborhood effects on sleep health rely on cross-sectional study designs with self-reported sleep measures and perceived neighborhood characteristics, which are susceptible to recall bias, same-source bias and reverse causality, and measurement errors. Due to these limitations, the causal identification and mechanisms still remain unclear. The present paper contributes to the existing literature by analyzing repeated measures of various objective measures of neighborhood characteristics and actigraphy-based sleep measures. We examined the association of the social neighborhood stressors with sleep health as well as investigated potential mediation via a psychological stress pathway.

Introduction

Sleep is an essential determinant of physical and mental health [1, 2]. A large body of studies show that sleep health is associated with body mass index [3], hypertension [4], type-2 diabetes [5], and other cardiovascular diseases [6]. Furthermore, poor sleep is related to multiple neurocognitive disorders [7, 8], as well as psychiatric illnesses [9-11]. Despite this, sleep duration, a key metric of sleep health, has been decreasing in the United States (U.S.) since 1960, and in 2014, more than 30% of U.S. population had short sleep duration, defined as sleep less than 7 hours [12]. In 2018, more than 35% of working adults in the U.S. reported insufficient sleep [13]. Sleep health outcomes, including sleep duration and sleep disorders, show socially patterned distributions related to sociodemographic factors, analogous to other chronic conditions [14, 15]. Specifically, Black population has higher burden of poor sleep health compared to their White counterpart [16-18]. Racial/ethnic minorities and lower socioeconomic groups are likely to reside in disadvantaged neighborhood environments, and such adverse environmental factors play important roles in the associations between neighborhood and sleep [19].

Neighborhood characteristics are important determinants of various health outcomes and health behaviors through different causal mechanisms [20-22]. Social environments of neighborhoods, such as safety and social cohesion, are particularly relevant to psychological well-being and mental health, as features of social disorders and neighborhood disadvantages function as salient stressors [23, 24]. Under the framework of the psychosocial theory, adverse neighborhood social characteristics may increase vulnerabilities to stress [25], and such increased stress may modify sleep behavior and sleep quality (Figure 1) [26]. In fact, social characteristics of neighborhoods are salient risk factors of perceived stress and psychological distress [27, 28], and various types of

stresses, such as allostatic load, stress biomarkers, and psychological distress, are associated with poor sleep health outcomes [29-32].

In addition to individual-level factors of sleep health including age, sex, race/ethnicity and occupation, growing evidence suggests that supra-individual and neighborhood-level factors, such as walkability, urban design, neighborhood disorder, safety and social cohesion, could shape sleep health [19, 33-37]. However, most of the studies on environmental risk factors of sleep health rely on cross-sectional study designs with self-reported sleep measures and perceived neighborhood characteristics, which are susceptible to recall bias, same-source bias and reverse causality, and measurement errors. Self-reported sleep health, commonly operationalized as sleep duration and sleep disturbances, may not capture various aspects of sleep, since sleep is a comprehensive and complex behavior with multi-faceted components including sleep timing, duration, quality, and circadian rhythm [38]. Perceived neighborhood conditions measured from survey are limited in translating the study findings in terms of designing feasible place-based interventions, as the perception is difficult to quantify and unable to locate actual points of interventions to improve neighborhood conditions. In addition, most existing studies on neighborhood and sleep examined residence-based neighborhood characteristics with static administrative boundaries posing potential biases, such as spatial misclassification and modifiable areal unit problems [39]. Recently, Johnson and colleagues investigated neighborhood social characteristics characterized by social cohesion and safety as determinants of objective sleep duration measured via actigraphy device (i.e. monitoring sleep/active cycles via wristwatch-like accelerometer devices) which have been validated to evaluate sleep and wake patterns [40-42]. Troxel and colleagues examined the associations between various social and physical characteristics of neighborhoods and sleep health

utilizing objective measures of sleep health via actigraphy device as well as quantitative neighborhood environment measures based on geographic information systems (GIS) [43-45]. However, the previous studies are still limited to cross-sectional study designs [43].

Due to the abovementioned limitations, the causal identification and mechanisms still remain unclear. Although there are cumulative evidences on psychological influences on sleep health [46], only a few cross-sectional studies investigated these variables as a potential causal mechanism between neighborhood and sleep [26, 45]. As there may be multiple direct and indirect pathways in the association, identification of causal mechanisms is important to provide plausible and feasible points of interventions to improve sleep health, especially in case of limited resources to improve neighborhood conditions [47]. Thus, it is critical to identify specific pathways of the impacts of neighborhood characteristics on sleep health, based on refined neighborhood assessments, psychological measures, and objective measures of sleep health, along with appropriate study design and statistical analysis [35].

The present paper contributes to the existing literature by analyzing repeated measures of various objective measures of neighborhood characteristics and actigraphy-based sleep measures. We hypothesized that adverse social environments in residential areas are positively associated with poor sleep health, and that the association between neighborhood environments and sleep health is mediated by psychological distress. The present paper aims to explore the association of the social neighborhood stressors with sleep health and examine potential mediation via a psychological stress pathway.

Methods

Data

The PHRESH Sleep (PHRESH Zzz) is a sub-cohort study based on an original study of Pittsburgh Hill/Homewood Research on Eating, Shopping, and Health (PHRESH). The participants of PHRESH study were recruited from a random sample of households in two low-income, predominantly African American neighborhoods in Pittsburgh, Pennsylvania [48]. From 2013, one neighborhood (the Hill District) has undergone significant neighborhood revitalization projects compared with the other neighborhood (Homewood), which included housing and greenspace improvements as well as retail and business developments. Such neighborhood investments allowed us to capture changes in neighborhood conditions within the study period providing enough spatial and temporal variations to examine the hypothesized association. The PHRESH Zzz investigated how and to what extent changes in social and built environments may impact sleep and other health behaviors. The PHRESH Zzz data were collected in 2013, 2016, and 2018 from an in-person household survey. There were 1051 participants who were in the cohort in 2013, 828 participants in 2016, and 820 in 2018 resulted in 22% attrition rate which is similar with other longitudinal actigraphy studies [49, 50]. Participants with fewer than 4 nights of actigraphy data ($n = 224$) and/or who were missing covariates ($n = 16$) were excluded from the analysis. It is assumed that the missingness of actigraphy data is mainly due to the adherence to the data collection protocols (e.g. continuous monitoring during 7 days) [51], and the socio-demographic characteristics of participants who had missing actigraphy data in Wave 2 and 3 were not significantly different from the complete cases (Table S3). Such missing not at random but suspected to depend on unobserved values would be preferred to be handled as a complete case analysis [52]. In addition, the analytic sample for mediation analysis included 570 participants who

completed all the three waves of data collection (Table S2) to estimate random intercept and random slope.

The PHRESH Zzz data collection included micro-level street auditing on social and built environments characteristics 1-year prior to the actigraphy measures of sleep across the three waves in the two neighborhoods. This objective assessment employed validated audit tools, including the Systematic Pedestrian and Cycling Environmental Scan [53], St. Louis Analytic Audit Tool and Checklist [54], and Systematic Social Observation protocol [55] with modifications for emphasis on physical activity, sleep, and obesogenic behaviors [56]. The auditing process covered a 25% random sample (n=511) of all street segments (n=2,027) in each neighborhood, with additional oversamples of 85 street segments in the neighborhood in which revitalization projects were anticipated. One year prior to each wave of PHRESH Zzz (2011, 2015, and 2017), pairs of trained data collectors conducted comprehensive observations on various social and physical characteristics including urban design features, neighborhood disorders, and walkability measures. Detailed information on audit variables were described elsewhere [56]. Across waves, the majority of items in the street audit tools showed good to excellent agreement (> 75% agreement) based on Krippendorff's alpha [57] and percentage inter-observer agreement [58, 59]. Neighborhood characteristics from the street audit data were spatially joined to individuals based on average scores of street segments within or intersecting with 1/4-mile network buffers of each participants' residential addresses. Details of the street auditing data collection procedures are described elsewhere [56].

Sleep

In the PHRESH Zzz study, Actigraph GT3X model was used to define sleep health outcomes, which is a validated device to measure sleep and wake rhythms relative to polysomnography [60-62]. Participants were asked to wear the wrist device for 7 consecutive days. Data of participants who wore fewer than 4 nights were excluded from the analyses based on suggested nights of data required to establish reliable sleep patterns via actigraphy [63]. Sleep and wake patterns were derived using Cole-Kripke algorithm to calculate total sleep time, sleep efficiency, and wake-after sleep onset (WASO). Sleep outcomes were averaged across all nights of each assessment period [64].

Sleep duration (i.e. total sleep time) is the total amount of time spent sleeping during the participant's time in bed assessed by actigraphy. Sleep duration in each wave was calculated by averaging the valid actigraphy data of each participants. The averaged time of sleep was analyzed as a continuous variable. In addition, less than 6 hours of average sleep duration in each wave was classified as insufficient sleep and utilized as a dichotomized variable. The 6-hour cut-point was employed as it has been identified as more salient risk factor of health compared to 7-hour cut-point especially among populations who already had higher prevalence of insufficient sleep [65], as well as it has been widely used in national representative studies of U.S. adults [66, 67]. WASO was measured as the total number of minutes classified as awake after sleep onset based upon the Cole-Kripke algorithm. WASO was analyzed as a continuous variable. Sleep efficiency was defined as the total duration of sleep divided by the total time in bed based on self-reported sleep diaries and visual inspection of actigraphy records. Higher values of sleep efficiency indicate better sleep continuity. Sleep efficiency was analyzed as a continuous variable.

Psychological Distress

Psychological distress was measured from the Kessler 6 (K6) scale. The K6 consists of six questions about how often the participants had felt: 1) nervous; 2) hopeless; 3) restless; 4) depressed; 5) that everything was an effort; and 6) worthless during past 30 days. The response options were: ‘never’, ‘a little of the time’, ‘some of the time’, ‘most of the time’ and ‘all of the time’. Responses were scored in the range of 0 (‘never’) to 4 (‘all of the time’), generating a scale with a range of 0–24, which indicates the presence of mild to severe distress. A K6 score above 5 points was classified as moderate distress [68], and the dichotomized variable was utilized in the analysis. The K6 scale was measured during the home visit of each data collection wave followed by the consecutive monitoring of sleep duration and quality through actigraphy device. Therefore, there was sequential temporal order between the psychological distress measure and sleep measures. Of note, previous sleep could have contributed to both psychological distress and subsequent sleep measures, representing a major source of confounding, and we tested the associations between sleep health outcomes and subsequent psychological distress.

Neighborhood characteristics

Crime

Incident-level crime data provided by the City of Pittsburgh police department were extracted and geocoded (95% geocoding rate) for 2012, 2015, and 2017 which were one year prior to the in-person household survey. For each household, the total number of crimes that occurred within a 1/4-mile network distance were summed for each year using ArcGIS 10.2 software. The 1/4-mile network distance was considered as a “short walking distance”, and it was frequently used in prior

neighborhoods research [69, 70]. In addition to the total number of crimes, violence and property crimes were considered separately in a sub-analysis.

Social Cohesion

Participants' perceptions of social cohesion were assessed with a validated questionnaire made of five-item Likert-scale items, ranging from 1 (strongly agree) to 5 (strongly disagree). The questions include: "People in this neighborhood are willing to help their neighbors", "This is a close-knit neighborhood", "People in this neighborhood can be trusted", "People in this neighborhood generally don't get along with each other", "People in this neighborhood do not share the same values", and "People in this neighborhood look out for one another" [71, 72]. The average scale of the six questions were employed as a social cohesion index with higher scores indicating greater perceived social cohesion, and each item was also utilized separately for sub-analysis.

Neighborhood disorder

Neighborhood disorder measure was derived from the street audit data. The data collectors recorded physical conditions of each street segment that may indicate neighborhood disorders including presences of any litter on streets, any vacant lot or housing, bars on windows, and broken windows as well as perceived safety (by data collectors) on the street segment [73]. All neighborhood disorder items were summed for each street segment, and average scores for participants were calculated based on the 1/4-mile street network buffer. Higher scores indicate more neighborhood disorder, and each item was also analyzed separately in a sub-analysis.

Covariates

A set of individual-level sociodemographic variables identified as potential confounders between neighborhood characteristics and sleep health was included in the analysis as covariates. The covariates included age, sex, per capita annual household income (in \$1,000), education attainment (less than high school [referent], high school diploma, some college, and bachelor's degree or above), employment status (employed full-time, employed part-time, unemployed or retired), marital status (married or living with partner, never married, and widowed or separated), and family structure (any child(ren) in household). Additionally, the number of years lived in the current neighborhood was also included in the analysis.

Statistical Analysis

Descriptive statistics were provided to summarize data of the study. All measures in the analysis, including the characteristics of neighborhood social environments, psychological distress, and sleep health were measured repeatedly across three waves. All exposure measures (i.e. neighborhood social environments) were standardized and the z-score were used to facilitate interpretation across different models. The three waves of data were analyzed using g-estimation with structured nested mean models (SNMM), estimating the joint additive effect of each neighborhood characteristic on sleep health across all 3 waves [74]. In notation, the joint effects is defined as $E(Y_s^{a_t,0} - Y_s^{a_{t-1},0} | A = a_{t-1}, C = c_t)$, for all $s=1, \dots, T$ and all $t < s$ with covariate c . In other words, the joint effect is the counterfactual outcome with exposure set to the observed up to time t and 0 afterwards, estimating expected effect (e.g. causal mean difference) of exposure at any time t on all subsequent outcome periods. For this analysis, it is assumed that the exposure at each time has the same effect on all subsequent outcomes, as the time period of data collection

was relatively short. Given the time interval between data collection years (three years on average), the effect of social environments at prior time can consistently affect the sleep health [75, 76]. When Y is a binary outcome (e.g. insufficient sleep), an SNMM fits the causal risk ratio [77]. Lastly, percentile-based confidence intervals for the causal parameters of a fitted SNMM were calculated from 500 bootstrapping samples.

To examine the mediating role of psychological distress averaged across three waves, natural direct and indirect effects were estimated using a potential outcomes frame which allows for an interaction between the exposure and the mediator [78]. To define the direct and indirect effects, let A denote an exposure variable (e.g. neighborhood characteristics), Y an outcome variable (e.g. insufficient sleep), M a mediator variable (e.g. psychological distress). Under this notation, the direct effect is the effect $A \rightarrow Y$, not through M, and the indirect effect is the effect $A \rightarrow M \rightarrow Y$.

The conditional natural direct/indirect effects are defined as $E(Y_{ij}^{a, M_{ij}^{a^*}} - Y_{ij}^{a^*, M_{ij}^{a^*}} | C_{ij} = c)$, and $E(Y_{ij}^{a, M_{ij}^a} - Y_{ij}^{a, M_{ij}^{a^*}} | C_{ij} = c)$, where $Y^{a, M^{a^*}}$ denotes the potential outcome that would have been observed if A were set to a and M were set to the value it would have taken if A were set to a^* . To establish valid mediation analyses, the following criteria were considered: a) if there was an association between exposure and mediator; and b) if there was an association between mediator and outcome. In addition, natural direct and indirect effects require following underlying assumptions: no unmeasured confounding between A – Y (denoted as C_1), no unmeasured confounding between A – M (denoted as C_2), no unmeasured confounding between M – Y (denoted as C_3), and no measured or unmeasured confounder between M – Y that itself affected by A (denoted as C_4). The abovementioned covariates were included to adjust for potential C_1 , C_2 , and C_3 , which included in all analysis (Figure 2). And the last assumption, C_4 , might be violated

due to the longitudinal data, as some covariates, especially indicators of socioeconomic status, might be affected by previous neighborhood social environments at prior timepoint [79-81]. Sleep measures at prior timepoint can also be associated with subsequent psychological distress and sleep measures (dotted arrow in Figure 2), and we tested the associations by employing lagged sleep health outcome (Equation 3). To pool within-wave mediation analysis across the three waves, two generalized mixed-effects models for both the mediator and the outcome were fitted. The model for the mediator has subject-specific random intercepts and random exposure slopes for each participant (Equation 1), and the outcome model has random intercepts and random slopes for the exposure, and the mediator (Equation 2).

$$\text{Equation 1} - M_{i,j} = \beta_0 + u_i + \beta_1 X_{1ij} + \dots + \beta_\rho X_{\rho ij} + \beta_{NBHD} NBHD_{ij} + \varepsilon_{ij}$$

$$\text{Equation 2} - Y_{i,j} = \gamma_0 + g_{0i} + \gamma_1 X_{1ij} + \dots + \gamma_\rho X_{\rho ij} + \gamma_{NBHD} NBHD_{ij} + \gamma_M M_{ij} + \eta_{ij}$$

where i corresponds to each participant and j to each visit; β_0 and γ_0 to the intercept for the sample mean; u_i and g_{0i} to the subject-specific random intercept. $\beta_1 X_{1ij}$ to $\beta_\rho X_{\rho ij}$ and $\gamma_1 X_{1ij}$ to $\gamma_\rho X_{\rho ij}$ correspond to the selected covariates. M_{ij} corresponds to psychological distress, and Y_{ij} corresponds to sleep health outcomes. $\beta_{NBHD} NBHD$ and $\gamma_{NBHD} NBHD$ correspond to neighborhood characteristics, and $\gamma_M M_{ij}$ corresponds to psychological distress in the mediator-outcome association. ε_{ij} and η_{ij} are the within-subject and within-visit error terms.

γ_{NBHD} corresponds to the natural direct effect, and the natural indirect effect is given by the product of $\beta_{NBHD} \times \gamma_M$. The delta method was used to calculate the variance of the natural indirect effect, which corresponds to $\text{Var}(\gamma_M) \beta_{NBHD}^2 + 2\text{Cov}(\beta_{NBHD}, \gamma_M) \beta_{NBHD} \gamma_M + \text{Var}(\beta_{NBHD}) \gamma_M^2$ [78]. Proportion mediated is calculated as the percentage of natural indirect effect over the total effect.

When fitting the linear mixed-effects models with subject-specific intercepts and covariate adjustment, we assumed no time-varying unmeasured confounding for M – Y relationship. However, socioeconomic status, such as income and employment status can be affected by previous social environments. In addition, sleep health outcomes at one visit could potentially affect psychological distress at the subsequent visit (dotted arrow in Figure 2), and it may potentially bias the mediator–outcome association and the mediation estimates [82, 83]. Therefore, we tested the presence of an association between Y^{ij} and M^{ij+1} , to check the assumption of the post-exposure M – Y confounding from Equation 3.

Equation 3 – $M_{i,j+1}$

$$= \alpha_0 + u_i + \alpha_1 X_{1ij} + \dots + \beta_\rho X_{\rho ij} + \alpha_Y Y_{1ij} + \alpha_M M_{ij} + \beta_{NBHD} NBHD_{ij} + \varepsilon_{ij}$$

where $M_{i,j+1}$ corresponds to psychological distress at subsequent visit.

All statistical analyses were performed using R software version 4.1.0, and ‘gesttools’ and ‘mediation’ packages were used for the G-estimation and mediation analysis [84, 85].

Results

There was a total of 2,699 participants in this study. The first wave in 2012 included 1,051 participants, and there were 828 participants for wave 2 in 2016, and 820 participants for wave 3 in 2018. Table 1 describes participant characteristics at each wave, and Table S2 shows 570 participants who completed all the three data collections. Ninety-two percent of participants were Black, and 76% were female at wave 1. The mean sleep duration was 344 minutes, and the prevalence of insufficient sleep (sleep duration < 6 hours) was 22% at the first wave.

Overall association between neighborhood social characteristics and sleep health

Table 2 show the joint associations of time-varying neighborhood social characteristics on sleep health. Crime rates within ¼-mile buffer of participants' home address were associated with increased risk of insufficient sleep (risk ratio (RR): 1.05, 95% confidence interval (CI) [1.02, 1.12]), increased WASO (risk difference (RD): 3.73 minutes, CI [0.26, 6.04]), and decreased sleep efficiency (RR:-0.55 percent point, CI [-0.92, -0.09]). For example, one standard deviation increases in crime rate (18.1 crimes in a year) within ¼-mile buffer around home can enhance the risk for insufficient sleep by 5%. Perceived social cohesion was associated with decreased risk of insufficient sleep (RR: 0.93, CI [0.88, 0.97]) and increased total sleep time (RD: 3.35 minutes, CI [0.88, 5.97]). Lastly, Neighborhood disorder indicators on streets within or intersecting ¼-mile buffer of participants home address was associated with decreased sleep efficiency (RD: -0.46 percent point, CI [-0.85, -0.77])

Mediation Analysis

Crime rate and social cohesion showed associations with psychological distress, however, neighborhood disorder was not associated with the mediator (Figure 3). Psychological distress was associated with insufficient sleep, WASO, and sleep efficiency, but not with sleep duration. Therefore, the basic criteria for valid mediation analysis for psychological distress (i.e. mediator) were met for crime, social cohesion as exposures, and insufficient sleep, WASO, and sleep efficiency as outcomes.

In addition, prior to fitting mixed effect models for the longitudinal mediation analysis, we examined whether there was time-varying confounding for the M-Y association due to previous sleep outcomes from equation 3 (dotted arrow in Figure 2). The psychological distress measure at the subsequent visit ($M_{ij} + 1$) was not associated with sleep health outcomes (Y_{ij}) at the prior visit, and all the point estimate and confidence interval were negligible (Table S1). However, other time-varying confounders, specifically covariates for socioeconomic status, still remain as potential sources of bias.

Table 3 presents the natural direct/indirect effects and proportion mediated for psychological distress. The results showed that psychological distress mediated the associations between crime rate in 1/4-mile network buffer and insufficient sleep, as well as between social cohesion score and insufficient sleep (figure 4 – a). Psychological distress was also a salient mediator in the relationships between crime and WASO (figure 4 – b), and between crime and sleep efficiency (figure 4 – c).

Discussion

We found associations between neighborhood social characteristics and objective measures of sleep health, consistent with previous findings [42, 43, 86]. Although it is not possible to directly compare the results due to the inconsistent constructs of neighborhood measures (e.g. 6-item social cohesion index vs. 4-item index or perceived safety vs. crime rate) as well as different sleep measures from other studies, our results showed similar directions of effects and sizes. The effects sizes from other large-scale studies may be greater than our findings, as our study site was geographically homogeneous local area, whereas the differences in neighborhood characteristics

would be wider in such large studies. By focusing on the local area, we were able to examine objectively measured micro-level neighborhood conditions from street auditing, facilitating the translation and implementation of potential place-based interventions. Specifically, neighborhood crime was associated with increased risk of insufficient sleep, increased WASO, as well as decreased sleep efficiency. One standard deviation increases (18 crimes/year in ¼-mile buffer around home) were associated with 5% increased risk for insufficient sleep, 3.7 minutes increased WASO, and -0.55% point decrease in sleep efficiency. Neighborhood social cohesion may be a protective factor of insufficient sleep and sleep duration, and lastly, neighborhood disorder, measured from audit items such as litters, broken windows, and/or vacant lots on streets, may decrease sleep efficiency in the two low-income, predominantly Black neighborhoods (e.g. 1.2 more indicators of neighborhood disorder in ¼-mile buffer were associated with -0.5 percent point decrease in sleep efficiency).

In addition, the mediation analyses found that psychological distress may play a minor but non-negligible role in the associations between neighborhood social characteristics and sleep health. The associations of neighborhood social cohesion with insufficient sleep was also partially explained by psychological distress. Previous research examined the impacts of neighborhood safety and social cohesion on psychological distress and self-reported sleep duration [26, 45, 87], and our findings support the mediating role of psychological distress.

We enhanced prior research on neighborhood effects on sleep health by utilizing repeated measures of neighborhood characteristics and sleep health with appropriate analytic approaches. Along with the g-estimation based on structured nested mean model, the three waves of PHRESH

Zzz data allows rigorous estimations of time-varying neighborhood characteristics and sleep health. In addition, the mediation analysis investigated a potential causal mechanism through psychological distress based on validations of potential confounding and biases. Lastly, except the perceived social cohesion index, the measures of neighborhood social characteristics (i.e. crime rates and neighborhood disorders) were captured via systematic report data and direct observations, which fully utilized the recent changes in the neighborhood due to redevelopment efforts.

Marginalized groups are likely to reside in disadvantaged environments, and such deprived social characteristics of neighborhoods have bearings on various health outcomes [20-22, 88]. Considering the associations between sleep and health [3-11], our findings suggests that disadvantaged neighborhood environments may play its role in health disparities in cardiometabolic diseases and other chronic conditions through sleep health in racial minority groups [89]. Thus, public health professionals and policy makers may consider neighborhood disorder, exposure to crimes, and perception of safety as key, modifiable, neighborhood factors that could address the poor sleep health as well as other sleep-related chronic conditions. From our analysis, we found that adverse neighborhood environments may increase psychological distress which may consequently contribute to sleep. These findings suggest place-based interventions that can enhance safety and social cohesion of a neighborhood. However, it should be interpreted with a caveat: reducing crime is not necessarily entails enforced policing [90]. For instance, increased level of social cohesion may also reduce crime rate,[91, 92] therefore a set of upstream strategies to foster social capital and collective efficacy in a neighborhood may be beneficial.[72, 93]

This study is not without limitations. Various neighborhood characteristics, including social and built environments, can effect changes in each other and consequently impact on sleep health. For instance, poor sidewalk conditions with abandoned buildings and empty lots may affect the sense of social cohesion in neighborhoods, and it is also possible that low social cohesion can cause poor maintenance of streets. Such interwoven associations between social and built environments are hardly separable from observational data [94]. We did not adjust for aspects of the built environment, so these represent unmeasured confounders that may bias our results. However, we assumed that social characteristics of neighborhoods are salient stressors which directly affect psychological distress as a distinct causal pathway and analyzing separate aspects of social environments can predict the total effect of each domain. In addition, there is might be unmeasured post-exposure confounders on the association between psychological distress and sleep health [95], which is a violation of underlying assumption for natural direct and indirect effects. For example, neighborhood characteristics may impact on the level of physical activity of individuals, and such physical inactivity can cause psychological distress as well as sleep health. Given the longitudinal nature of the data, there are also measured post-exposure confounders, including the current wave's covariates. If any one of these measured variables or any additional unmeasured variables acted as a post-exposure confounder, the natural direct and indirect effects would not be identified, and our results could be biased. However, we hypothesize that the selected covariates were potential determinants of social characteristics of neighborhoods, rather than consequences of neighborhood environments. An alternative would be to estimate interventional direct and indirect effects, which do not need such an assumption for identification. In this analysis, the baseline sleep outcomes and psychological distress measures were not measured nor included as covariates,

which may result biased estimates. However, baseline adjustment with potential measurement errors can also cause additional biases [96].

We utilized participants' residential address which does not capture of daily mobility-based neighborhood exposures [97]. For example, individuals are exposed to multiple (e.g. residential, work, socializing) neighborhood environments in their daily lives, thus adequate capture of neighborhood characteristics based on daily mobility pattern is important in determining actual exposures to neighborhood characteristics. In addition, residential self-selection of individuals, referring individuals' propensity to choose where to live based on their life needs and preferences, may influence the neighborhood satisfaction and sleep [98].

This study was conducted in relatively small neighborhood areas, Hill District and Homewood in Pittsburgh, and such small geographic variations are unlikely to represent diverse environmental factors across large cities. Thus, the study results may not be generalizable to other urban or rural contexts. However, as one of the neighborhoods, Hill District, experienced community-wide urban redevelopment projects, and the findings may suggest the associations of urban development changes with sleep health in large metropolitan areas. Also, the time period of study was relatively short to detect the differential effects of social environments on sleep across stages of life-course, and the effects detected would only be applicable to the specific age group of the study. Although actigraphy data have strengths in measuring sleep health objectively, it has limitations, such as imperfect capture of sleep health due to dropping out participants with less than 4 night thus. Given the exclusion, the present analysis may not fully represent the characteristics of the PHRESH Zzz data.

Lastly, it is important to note that the K6 measure does not broadly capture neighborhood stressors but is used for detecting serious mental illness and disorders. Moreover, social cohesion was

assessed with an individual subjective measure rather than with an objective collective measure as those provided by econometric analyses of residents' perceptions [99].

In summary, we found the social characteristics of neighborhoods are related to actigraphy-based sleep health measures via a potential psychological pathway. Since sleep is a salient determinant of several poor health outcomes including obesity, cardiovascular diseases, and psychiatric illnesses, improving sleep health may subsequently affect a variety of public health challenges. Based on our findings, interventions to improve sleep should target modifiable factors and enhance neighborhood environments. These sorts of strategies have the potential to improve not only sleep health but also other health outcomes.

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Figure 1. Conceptual Diagram

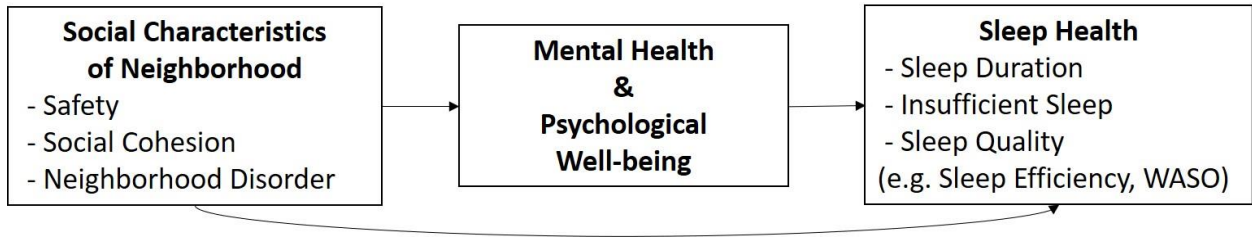


Figure 2. Directed acyclic graph (DAG) for mediation analysis. $A_{i,j}$ represents neighborhood characteristics for i th subject at j th visit; $M_{i,j}$ represents psychological distress for i th subject at j th visit; $Y_{i,j}$ represents sleep health outcomes for i th subject at j th visit. $C_{i,j}^{1,2,3}$ represents exposure outcome confounders (C_1), exposure mediator confounders (C_2), and mediator outcome confounders (C_3). Arrows from j to $j+1$ were omitted for readability

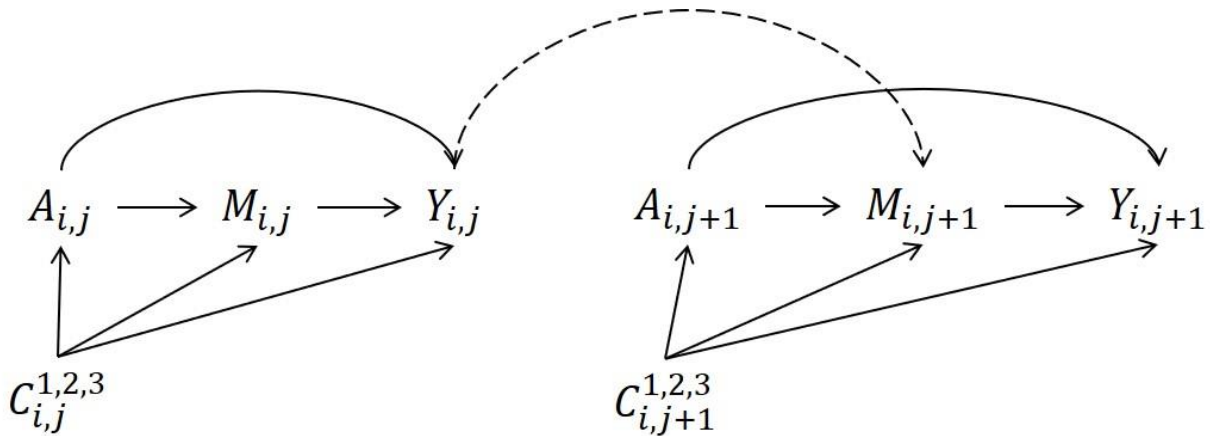


Figure 3. Exposure-mediator and mediator-outcome associations. Each mixed-effect regression models were adjusted for age, sex, income, education, employment, marital status, family structure, and number of years in current neighborhood.

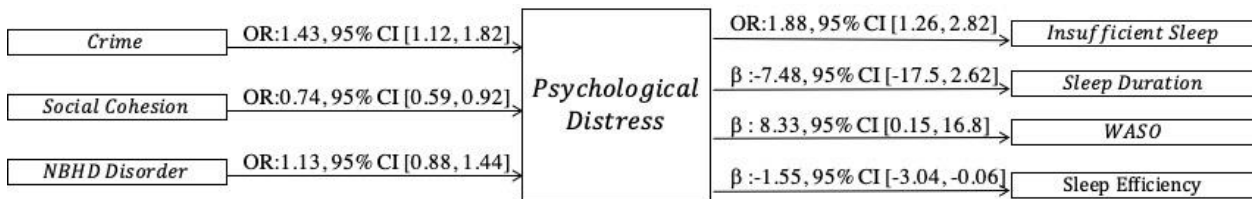
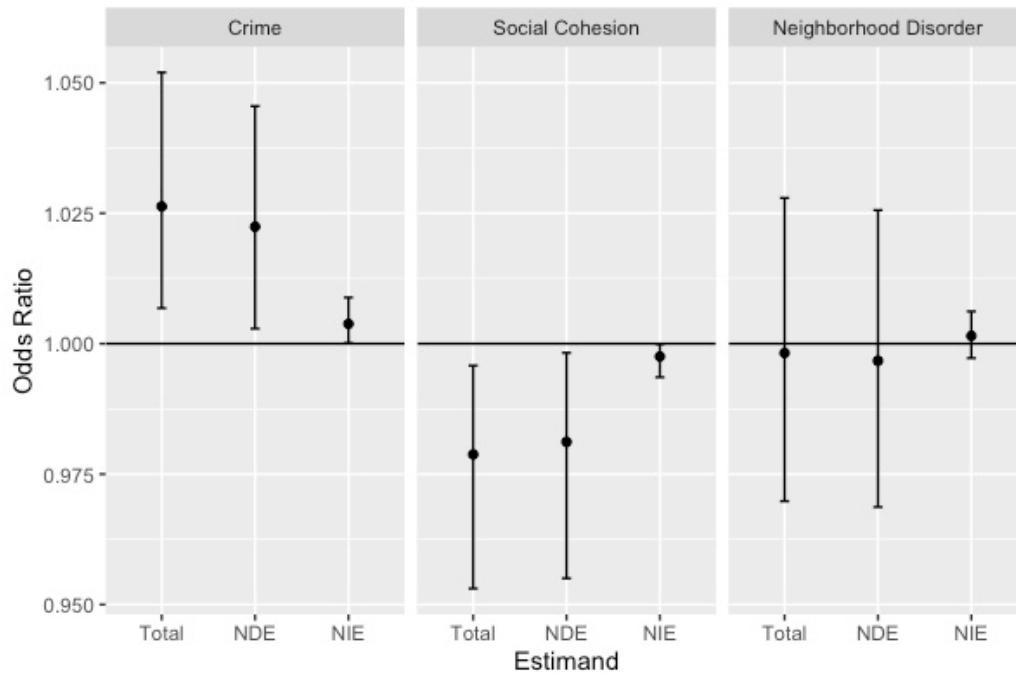
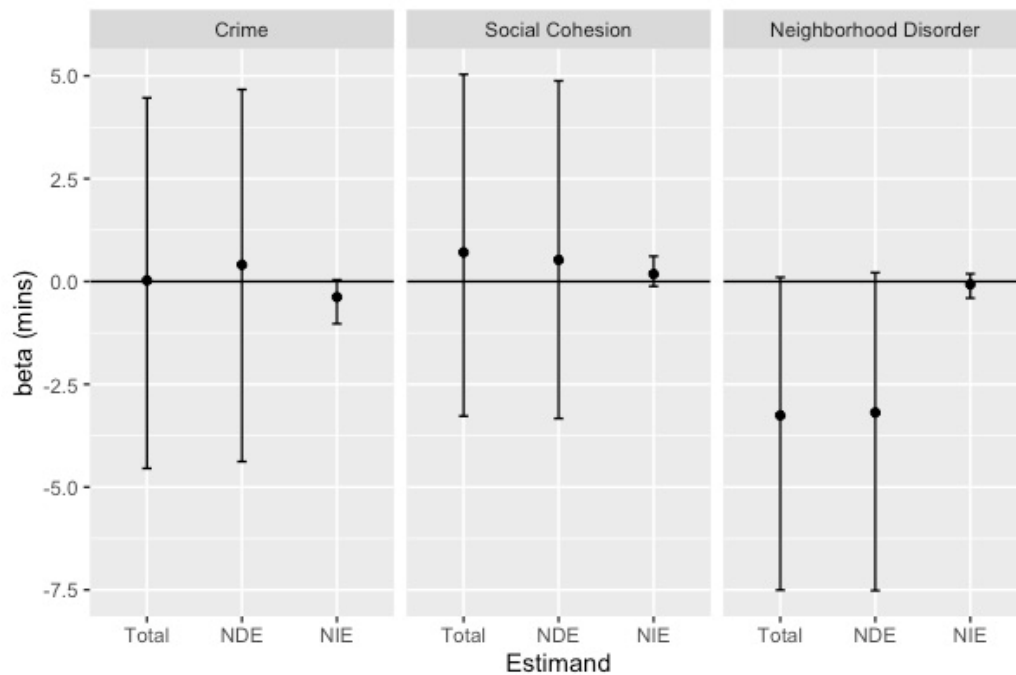


Figure 4. Mediation analysis results. Figure 4-a is for insufficient sleep, 4-b for sleep duration, 4-c for WASO, and 4-d for sleep efficiency outcomes. Each plot represents the four built environment characteristics. Total: total effect, NDE: natural direct effect, NID: natural indirect effect

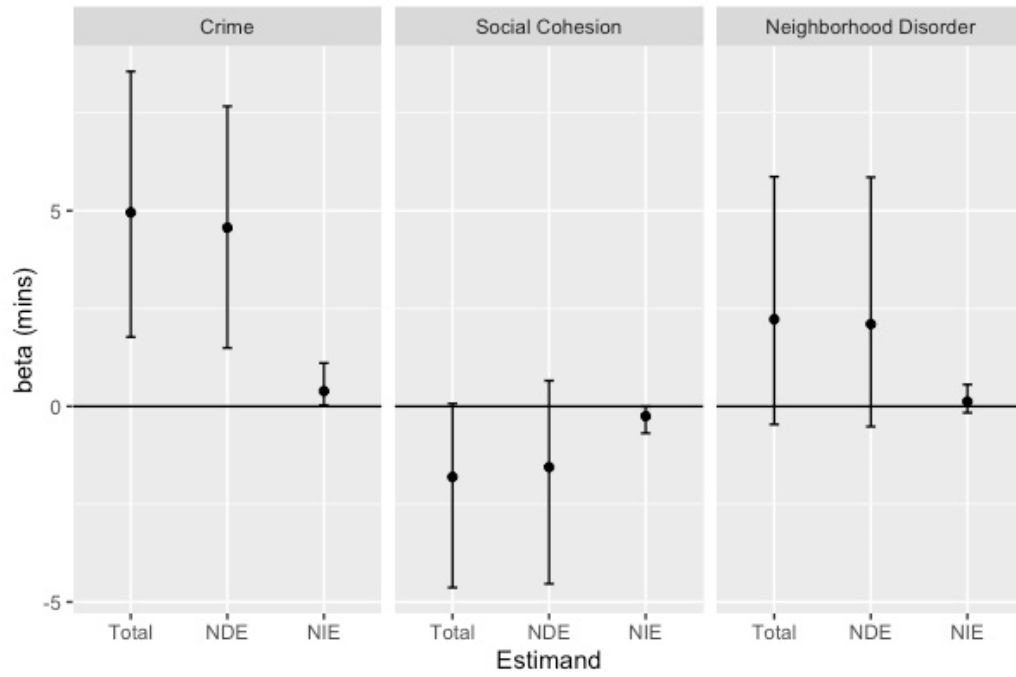
(4-a). Insufficient Sleep



(4-a). Sleep Duration



(4-c). WASO



(4-d). Sleep Efficiency

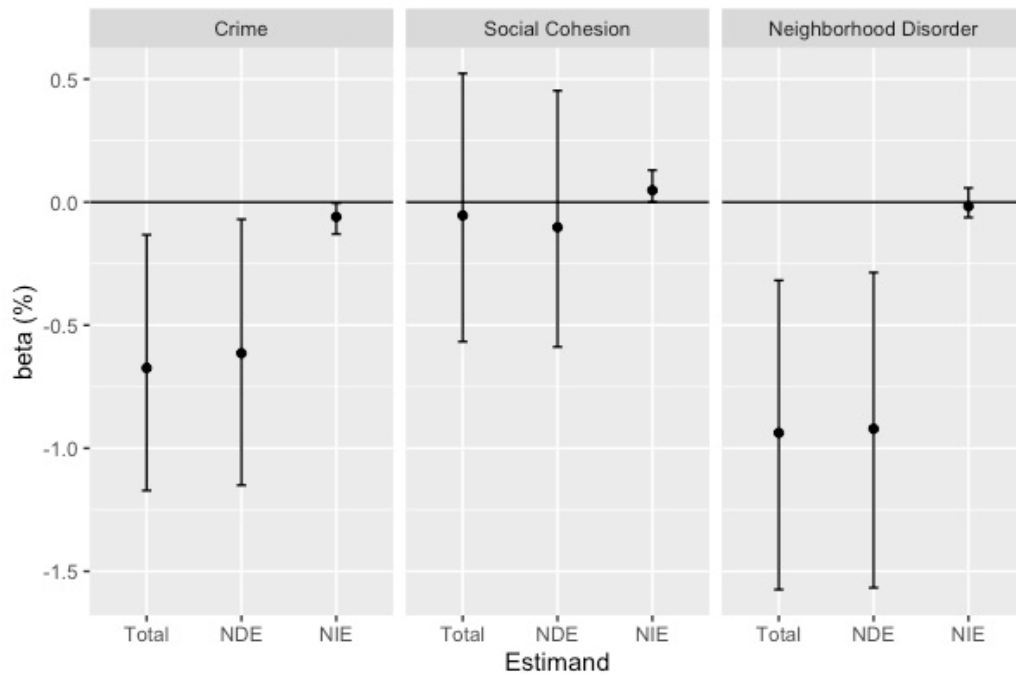


Table 1. PHRESH Zzz Study Characteristics

	PHRESH Zzz					
	2012 (n=1,051)		2016 (n=828)		2018 (n=820)	
	Mean or count	SD or %	Mean or count	SD or %	Mean or count	SD or %
Age	54.6	16.5	57.9	15.5	59.8	15.0
Race						
African-American	963	91.6%	765	92.4%	734	89.5%
Non African-American	88	8.4%	63	7.6%	86	10.5%
Female	803	76.4%	656	79.2%	658	80.2%
Per capita annual household income (in 1,000)	13.5	13.9	14.0	13.5	14.3	14.1
Education						
Less than high school	145	13.8%	104	12.6%	89	10.9%
High school	432	41.1%	348	42.0%	311	37.9%
Some college	324	30.8%	264	31.9%	318	38.8%
College	150	14.3%	112	13.5%	102	12.4%
Marital status						
Married or living with partner	212	20.2%	137	16.5%	123	15.0%
Never married	417	39.7%	349	42.1%	351	42.8%
Widowed, divorced or separated	422	40.2%	342	41.3%	346	42.2%
Household with child(ren)	290	27.6%	207	25.0%	172	21.0%
Employment						
Full-time	245	23.3%	195	23.6%	179	21.8%
Part-time	142	13.5%	117	14.1%	110	13.4%
Not employed	664	63.2%	516	62.3%	531	64.8%
Years in current neighborhood	29.7	23.3	28.5	22.5	31.6	23.0
Sleep health						
Mean minutes sleep duration	344	84.7	334	77.5	327	82.5
Insufficient sleep (<6hr)	229	21.8%	201	24.3%	208	25.4%
Mean minutes of WASO	88.8	54.1	111	62.6	123	71.5
Mean sleep efficiency (%)	78.0	11.2	73.0	11.9	70.8	12.6
Psychological distress (K6 score \geq 5)	217	20.6%	168	20.3%	160	19.5%
Total crime (in ¼-mile buffer)	23.1	18.1	23.7	17.5	23.9	21.0
Social cohesion score	3.06	0.81	3.16	0.77	3.26	0.74
Neighborhood disorder score (in ¼-mile buffer)	4.66	1.21	4.82	1.10	4.54	1.0

Table 2. Joint causal effects of neighborhood social characteristics on sleep health

Exposure	Outcome	Risk Ratio (or Risk Difference)	95% Confidence Interval
Crime	Insufficient Sleep	1.05	(1.02, 1.12)*
	Total Sleep	-1.22	(-3.79, 1.48)
	WASO	3.73	(0.26, 6.04)*
	Sleep Efficiency	-0.55	(-0.92, -0.09)*
Social Cohesion	Insufficient Sleep	0.93	(0.88, 0.97)*
	Total Sleep	3.35	(0.88, 5.97)*
	WASO	-0.61	(-2.86, 1.47)
	Sleep Efficiency	0.07	(-0.3, 0.49)
Neighborhood Disorder	Insufficient Sleep	0.99	(0.94, 1.07)
	Total Sleep	-0.99	(-3.95, 2.58)
	WASO	1.61	(-0.6, 4.42)
	Sleep Efficiency	-0.46	(-0.85, -0.07)*

All models were adjusted for age, sex, education, marital status, family structure, and number of years in current neighborhood.

Table 3. Mediation Analysis Results (complete case analysis)

	Insufficient Sleep		Sleep Duration		WASO		Efficiency	
	ORs	95% CI	β	95% CI	β	95% CI	β	95% CI
Crime								
Total	1.03	(1.01, 1.05)*	0.03	(-4.55, 4.47)	4.96	(1.77, 8.56)*	-0.67	(-1.17, -0.13)*
NDE	1.02	(1.00, 1.05)*	0.41	(-4.38, 4.67)	4.57	(1.49, 7.67)*	-0.61	(-1.15, -0.07)*
NIE	1.00	(1.00, 1.01)*	-0.38	(-1.03, 0.04)	0.39	(0.03, 1.11)*	-0.06	(-0.13, 0.00)*
Proportion Mediated	0.13	(-0.02, 0.42)	0.02	(-2.35, 3.22)	0.08	(0.01, 0.3)*	0.09	(0.00, 0.57)*
Social Cohesion								
Total	0.98	(0.95, 1.00)*	0.71	(-3.27, 5.04)	-1.80	(-4.63, 0.07)	-0.05	(-0.57, 0.52)
NDE	0.98	(0.96, 1.00)*	0.52	(-3.33, 4.88)	-1.55	(-4.54, 0.66)	-0.10	(-0.59, 0.45)
NIE	1.00	(0.99, 1.00)*	0.18	(-0.12, 0.61)	-0.25	(-0.69, -0.01)*	0.05	(0.00, 0.13)*
Proportion Mediated	0.08	(-0.06, 0.66)	0.05	(-0.65, 4.51)	0.13	(-0.26, 3.16)	-0.02	(-3.3, 9.49)
Neighborhood Disorder								
Total	1.00	(0.97, 1.03)	-3.26	(-7.51, 0.10)	2.23	(-0.46, 5.87)	-0.94	(-1.57, -0.32)*
NDE	1.00	(0.97, 1.03)	-3.19	(-7.52, 0.22)	2.10	(-0.52, 5.86)	-0.92	(-1.57, -0.29)*
NIE	1.00	(1.00, 1.01)	-0.07	(-0.40, 0.19)	0.12	(-0.16, 0.56)	-0.02	(-0.06, 0.06)
Proportion Mediated	0.01	(-1.39, 2.52)	0.01	(-0.11, 0.34)	0.04	(-0.09, 8.35)	0.02	(-0.07, 0.09)

NDE: Natural Direct Effect, NIE: Natural Indirect Effect, *:p-value<0.05

All models were adjusted for age, sex, education, marital status, family structure, and number of years in current neighborhood.

Table S1. Associations of sleep health outcomes with psychological distress at the subsequent visit (t + 1)

Neighborhood Characteristic	Sleep at t	Psychological Distress at t+1	95% CI
Crime	Insufficient Sleep	0.92	(0.6, 1.39)
	Sleep Duration	1.00	(1.00, 1.00)
	WASO	1.00	(1.00, 1.00)
	Sleep Efficiency	0.99	(0.98, 1.01)
Social Cohesion	Insufficient Sleep	0.94	(0.62, 1.41)
	Sleep Duration	1.00	(1.00, 1.00)
	WASO	1.00	(1.00, 1.00)
	Sleep Efficiency	0.99	(0.98, 1.01)
Neighborhood Disorder	Insufficient Sleep	0.96	(0.62, 1.48)
	Sleep Duration	1.00	(1.00, 1.00)
	WASO	1.00	(1.00, 1.00)
	Sleep Efficiency	0.99	(0.98, 1.01)

Table S2. PHRESH Zzz Study Characteristics – Complete Cases Only

	PHRESH Zzz (n=570)					
	2012		2016		2018	
	Mean or count	SD or %	Mean or count	SD or %	Mean or count	SD or %
Age	55.8	14.2	58.9	14.1	61.6	14.2
Race						
African-American	536	94%	536	94%	536	94%
Non African-American	34	6%	34	6%	34	6%
Female	463	81.2%	463	81.2%	463	81.2%
Per capita annual household income (in 1,000)	14.1	14.3	14.6	13.6	15.2	15.1
Education						
Less than high school	71	12.5%	71	12.5%	63	11.1%
High school	242	42.5%	242	42.5%	219	38.4%
Some college	180	31.6%	180	31.6%	212	37.2%
College	77	13.5%	77	13.5%	76	13.3%
Marital status						
Married or living with partner	110	19.3%	91	16.0%	84	14.7%
Never married	234	41.1%	241	42.3%	238	41.8%
Widowed, divorced or separated	226	39.6%	238	41.8%	248	43.5%
Household with child(ren)	140	24.6%	119	20.9%	98	17.2%
Employment						
Full-time	137	24.0%	124	21.8%	127	22.3%
Part-time	81	14.2%	84	14.7%	76	13.3%
Not employed	352	61.8%	362	63.5%	367	64.4%
Years in current neighborhood	32.5	22.4	29.4	21.9	33.2	23.1
Sleep health						
Mean minutes sleep duration	342	80.5	334	74.5	327	82.4
Insufficient sleep (<6hr)	130	22.80%	143	25.10%	167	29.30%
Mean minutes of WASO	88	55.9	112	64.1	123	73.5
Mean sleep efficiency (%)	78.3	10.8	73	11.8	71.1	12.3
Psychological distress (K6 score ≥ 5)	116	20.4%	111	19.5%	105	18.4%
Total crime (in ¼-mile buffer)	23.2	17.7	24.1	18.0	23.8	21.4
Social cohesion score	3.06	0.81	3.18	0.79	3.27	0.76
Neighborhood disorder score (in ¼-mile buffer)	4.57	1.23	4.75	1.11	4.49	1.0

Table S3. Comparison of participants with missing actigraphy data

mean or count (SD or %)	Complete case (n=832)	Missing (n=219)	p-value*
Age (year)	55.01 (16.24)	53.16 (17.36)	0.14
Female (%)	643 (77.3)	160 (73.1)	0.22
Income (\$1,000)	13.23 (13.13)	14.30 (16.55)	0.31
Education (%)			0.43
Less than high school	110 (13.2)	35 (16.0)	
High school	352 (42.3)	80 (36.5)	
Some college	252 (30.3)	72 (32.9)	
College	118 (14.2)	32 (14.6)	
Marital status (%)			0.33
Married or with partner	173 (20.8)	39 (17.8)	
Never married	321 (38.6)	96 (43.8)	
Widowed, divorced, separated	338 (40.6)	84 (38.4)	
Household with child(ren) (%)	228 (27.4)	62 (28.3)	0.86
Employment (%)			0.56
Full-time	189 (22.7)	56 (25.6)	
Part-time	116 (13.9)	26 (11.9)	
Not employed	527 (63.3)	137 (62.6)	

* T-test for continuous variables and χ^2 test for categorical variables