SLEEP, 2022, 1–12

https://doi.org/10.1093/sleep/zsac087
Advance Access Publication Date: 14 April 2022
Original Article

ORIGINAL ARTICLE

Mediating role of psychological distress in the associations between neighborhood social environments and sleep health

Byoungjun Kim[1,2,*], Wendy M. Troxel[3], Tamara Dubowitz[3], Gerald P. Hunter[3], Bonnie Ghosh-Dastidar[3], Basile Chaix[4], Kara E. Rudolph[1], Christopher N. Morrison[1,5], Charles C. Branas[1] and Dustin T. Duncan[1]

[1]Department of Epidemiology, Columbia University Mailman School of Public Health, New York, NY, USA, [2]Department of Population Health, New York University Grossman School of Medicine, New York, NY, USA, [3]Health Division, RAND Corporation, Pittsburgh, PA, USA, [4]Sorbonne Université, INSERM, Institut Pierre Louis d'Epidémiologie et de Santé Publique IPLESP, Nemesis Team, Paris, France and [5]Department of Epidemiology and Preventive Medicine, School of Public Health and Preventive Medicine, Monash University, Melbourne, VIC, Australia

*Corresponding author. Byoungjun Kim, Department of Population Health, New York University Grossman School of Medicine, 180 Madison Ave 5th Floor, New York, NY 10016, USA. Email: byoungjun.kim@nyulangone.org.

Abstract

Study Objectives: The 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* = 2699), a longitudinal study conducted in two low-income, predominately Black neighborhoods, were utilized for this analysis. The 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 the 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.

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.

Key words: neighborhood; crime; social cohesion; neighborhood disorder; sleep; actigraphy; psychological distress; mediation analysis

Submitted: 24 November, 2021; **Revised:** 21 March, 2022

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 since 1960, and in 2014, more than 30% of the U.S. population had short sleep duration, defined as sleep less than 7 h [12]. In 2018, more than 35% of working adults in the United States 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, the 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, the social characteristics of neighborhoods are salient risk factors for 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 multifaceted components, including sleep timing, duration, quality, and circadian rhythm [38]. Perceived neighborhood conditions measured from the 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 positing potential biases, such as spatial misclassification and modifiable areal unit problems [39]. Recently, Johnson *et al.* 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 *et al.* examined the associations between various social and physical characteristics of neighborhoods and sleep health by 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].

Figure 1. Conceptual diagram.

Due to the abovementioned limitations, the causal identification and mechanisms still remain unclear. Although there are cumulative evidences of 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]. Since 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 to 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 for 7 days) [51], and the sociodemographic characteristics of participants who had missing actigraphy data in waves 2 and 3 were not significantly different from the complete cases (Supplementary 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 (Supplementary 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 before 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 = 2027) in each neighborhood, with additional oversamples of 85 street segments in the neighborhood in which revitalization projects were anticipated. One year before 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 ¼-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, the 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 participant. The averaged time of sleep was analyzed as a continuous variable. In addition, less than 6 h of average sleep duration in each wave was classified as insufficient sleep and utilized as a dichotomized variable. The 6-h cut-point was employed as it has been identified as a more salient risk factor for health compared to 7-h cut-point especially among populations who already had a 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 1 year prior to the in-person household survey. For each household, the total number of crimes that occurred within a ¼-mile network distance were summed for each year using ArcGIS 10.2 software. The ¼-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 5-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 was 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 the presence 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 ¼-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 $1000), 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 the 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 the 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 was 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 are defined as $E(Y_s^{a_t,0} - Y_s^{a_{t-1},0} | A = a_{t-1}, C = c_t)$, for all $s = 1,\ldots,T$ 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 the 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 (3 years on average), the effect of social environments at a 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 (RR) [77]. Lastly, percentile-based confidence intervals (CIs) 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 that 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), and 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 $E(Y_{ij}^{a,M_{ij}^{a^*}} - Y_{ij}^{a^*,M_{ij}^{a^*}} \mid C_{ij} = c)$, and $E(Y_{ij}^{a,M_{ij}^{a}} - Y_{ij}^{a,M_{ij}^{a^*}} \mid C_{ij} = c)$, 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 the 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 were included in all analyses (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 a prior timepoint [79–81]. Sleep measures at a 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 outcomes (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).

$$M_{i,j} = \beta_0 + u_i + \beta_1 X_{1ij} + \ldots + \beta_\rho X_{\rho ij} + \beta_{NBHD} NBHD_{ij} + \varepsilon_{ij} \tag{1}$$

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

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 $\beta_p X_{pij}$ and $\gamma_p X_{pij}$ to $\gamma_p X_{pij}$ 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

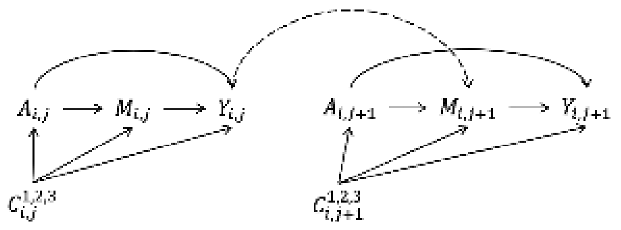

Figure 2. Directed acyclic graph (DAG) for mediation analysis. $A_{i,j}$ represents neighborhood characteristics for ith subject at jth visit; $M_{i,j}$ represents psychological distress for ith subject at jth visit; $Y_{i,j}$ represents sleep health outcomes for ith subject at jth visit. $C_{1,2,3i,j}$ 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.

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 $Var(\gamma_M)\ \beta_{NBHD}^2 + 2Cov(\beta_{NBHD}, \gamma_M)\ \beta_{NBHD}\ \gamma_M + Var(\beta_{NBHD})\ \gamma_M^2$ [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 $Y_{i,j}$ and $M_{i,j+1}$, to check the assumption of the post-exposure *M* – *Y* confounding from equation (3).

$$M_{i,j+1} = \alpha_0 + u_i + \alpha_1 X_{1ij} + \ldots + \beta_\rho X_{\rho ij} + \alpha_Y Y_{1ij} + \alpha_M M_{ij} + \beta_{NBHD} NBHD_{ij} + \varepsilon_{ij} \quad (3)$$

where $M_{i,j+1}$ corresponds to psychological distress at a 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 2699 participants in this study. The first wave in 2012 included 1051 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 Supplementary 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 min, and the prevalence of insufficient sleep (sleep duration <6 h) was 22% at the first wave.

Overall association between neighborhood social characteristics and sleep health

Table 2 shows 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 (RR: 1.05, 95% CI [1.02, 1.12]), increased WASO (risk difference [RD]: 3.73 min, CI [0.26, 6.04]), and decreased sleep efficiency (RR: –0.55% point, CI [–0.92, –0.09]). For example, one standard deviation increase in the 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 min, 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% 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, before fitting mixed-effects 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 estimates and CI were negligible (Supplementary Table S1). However, other time-varying confounders, specifically covariates for socioeconomic status, still remain as potential sources of bias.

Table 3 shows the natural direct/indirect effects and proportion mediated for psychological distress. The results showed that psychological distress mediated the associations between crime rate in ¼-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 effect 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

Table 1. PHRESH Zzz study characteristics

	PHRESH Zzz					
	2012 (*n* = 1051)		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 1000)	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 of sleep duration	344	84.7	334	77.5	327	82.5
Insufficient sleep (<6 h)	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 ≥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 the number of years in current neighborhood.

"*$p < 0.05$."

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 min 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% point decrease in sleep efficiency).

In addition, the mediation analyses found that psychological distress may play a minor but non-negligible role in the

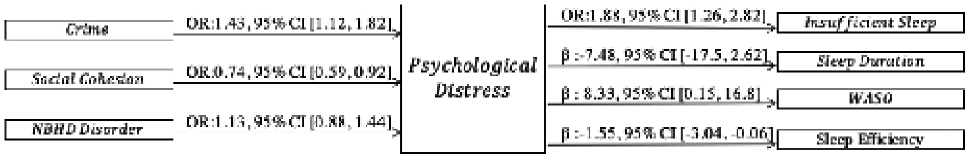

Figure 3. Exposure–mediator and mediator–outcome associations. Each mixed-effects regression model was adjusted for age, sex, income, education, employment, marital status, family structure, and the number of years in current neighborhood.

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)

Abbreviations: NDE, natural direct effect; NIE, natural indirect effect.
All models were adjusted for age, sex, education, marital status, family structure, and the number of years in current neighborhood.
*$p < .05$.

associations between neighborhood social characteristics and sleep health. The associations of neighborhood social cohesion with insufficient sleep were 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 SNMM, the three waves of PHRESH Zzz data allow 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 suggest that disadvantaged neighborhood environments may play a role in health disparities in cardiometabolic diseases and other chronic conditions through sleep health in racial minority groups [89]. Thus, public health professionals and policymakers 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 the 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 the 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 affect changes in each other and consequently impact 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 the social characteristics of neighborhoods are salient stressors that directly affect psychological distress as a distinct causal pathway, and analyzing separate aspects of social environments can predict the total effect of each

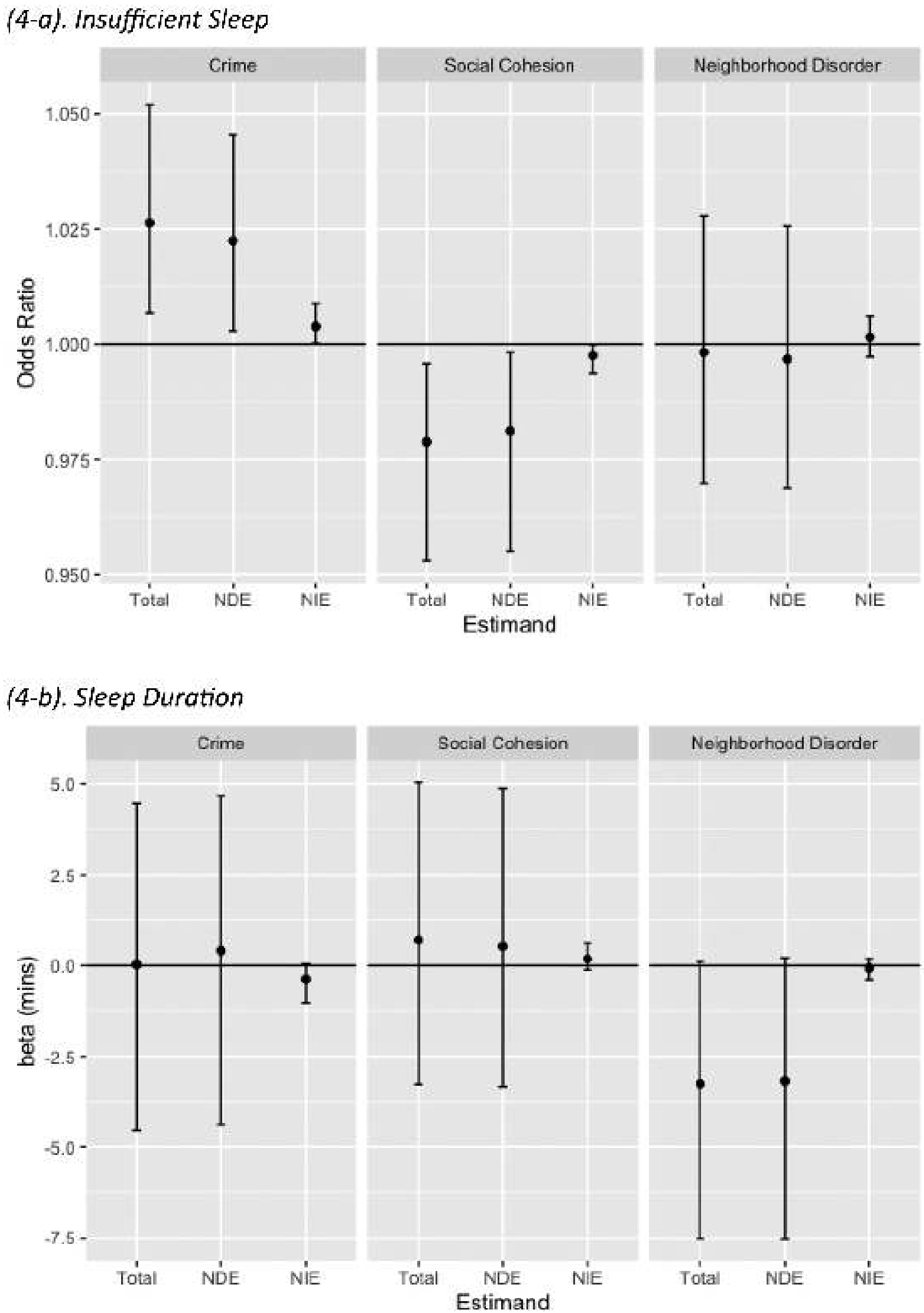

Figure 4. Mediation analysis results. 4-a is for insufficient sleep, 4-b for sleep duration, 4-c for WASO, and 4-d for sleep efficiency outcomes. Each plot represents the four built environment characteristics. Total, total effect, NDE, natural direct effect, NIE, natural indirect effect.

domain. In addition, there might be unmeasured post-exposure confounders in 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 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

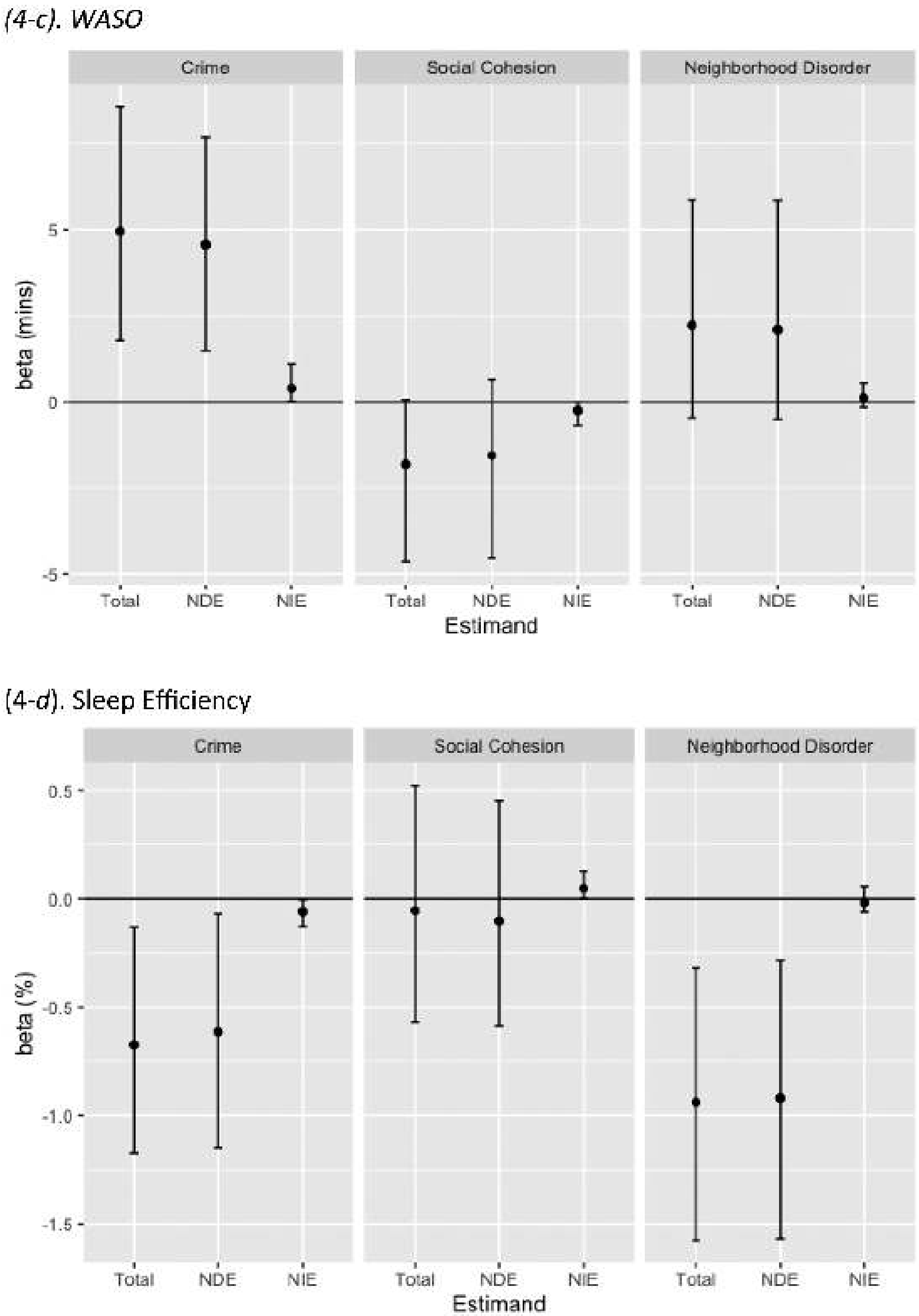

Figure 4. Continued.

our results could be biased. However, we hypothesize that the selected covariates were potential determinants of the 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 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 patterns 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, there are limitations, for instance, potential selection bias from excluding observations with less than 4 nights of actigraphy data. 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 ecometric 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.

Supplementary Material

Supplementary material is available at *SLEEP* online.

Funding

Funding for PHRESH Zzz study was provided by the National Heart Lung Blood Institute (Grant No. R01 HL122460 and HL131531) and the National Cancer Institute (Grant No. R01CA164137). Dr. Byoungjun Kim was supported in part by the NYU Training Program in Healthcare Delivery Science and Population Health funded by Agency for Healthcare Research and Quality (Grant No. T32HS026120; Leora Horwitz, MD and Mark Schwartz, MD, Principal Investigators).

Disclosure Statement

Financial disclosure: none.

Non-financial disclosure: none.

References

1. Czeisler CA. Duration, timing and quality of sleep are each vital for health, performance and safety. *Sleep Health*. 2015;**1**(1):5–8. doi:10.1016/j.sleh.2014.12.008.
2. Grandner MA, *et al*. Mortality associated with short sleep duration: the evidence, the possible mechanisms, and the future. *Sleep Med Rev*. 2010;**14**(3):191–203. doi:10.1016/j.smrv.2009.07.006.
3. Ford ES, *et al*. Sleep duration and body mass index and waist circumference among U.S. adults. *Obesity (Silver Spring)*. 2014;**22**(2):598–607. doi:10.1002/oby.20558.
4. Gangwisch JE, *et al*. Short sleep duration as a risk factor for hypertension: analyses of the first National Health and Nutrition Examination Survey. *Hypertension*. 2006;**47**(5):833–839. doi:10.1161/01.HYP.0000217362.34748.e0.
5. Cappuccio FP, *et al*. Quantity and quality of sleep and incidence of type 2 diabetes: a systematic review and meta-analysis. *Diabetes Care*. 2010;**33**(2):414–420. doi:10.2337/dc09-1124.
6. Mullington JM, *et al*. Cardiovascular, inflammatory, and metabolic consequences of sleep deprivation. *Prog Cardiovasc Dis*. 2009;**51**(4):294–302. doi:10.1016/j.pcad.2008.10.003.
7. Lim J, *et al*. A meta-analysis of the impact of short-term sleep deprivation on cognitive variables. *Psychol Bull*. 2010;**136**(3):375–389. doi:10.1037/a0018883.
8. Cohen DA, *et al*. Sleep and neurological disorders. In: Cappuccio FP, *et al*., eds. *Sleep, Health, and Society*. Oxford, UK: Oxford University Press; 2018:191–214.
9. Ford DE, *et al*. Epidemiologic study of sleep disturbances and psychiatric disorders. An opportunity for prevention? *JAMA*. 1989;**262**(11):1479–1484. doi:10.1001/jama.262.11.1479.
10. Benca RM, *et al*. Sleep and psychiatric disorders. A meta-analysis. *Arch Gen Psychiatry*. 1992;**49**(8):651–668; discussion 669-70. doi: 10.1001/archpsyc.1992.01820080059010.
11. Sateia MJ. Update on sleep and psychiatric disorders. *Chest*. 2009;**135**(5):1370–1379. doi:10.1378/chest.08-1834.
12. Liu Y, *et al*. Prevalence of healthy sleep duration among adults—United States, 2014. *MMWR Morb Mortal Wkly Rep*. 2016;**65**(6):137–141.
13. Khubchandani J, *et al*. Short sleep duration in working American adults, 2010–2018. *J Community Health*. 2020;**45**(2):219–227. doi:10.1007/s10900-019-00731-9.
14. Jackson CL, *et al*. Racial disparities in short sleep duration by occupation and industry. *Am J Epidemiol*. 2013;**178**(9):1442–1451. doi:10.1093/aje/kwt159.
15. Jackson CL. Determinants of racial/ethnic disparities in disordered sleep and obesity. *Sleep Health*. 2017;**3**(5):401–415. doi:10.1016/j.sleh.2017.08.001.
16. Jackson CL, *et al*. A workshop report on the causes and consequences of sleep health disparities. *Sleep*. 2020;**43**(8). doi:10.1093/sleep/zsaa037.
17. Chen X, *et al*. Racial/ethnic differences in sleep disturbances: the Multi-Ethnic Study of Atherosclerosis (MESA). *Sleep*. 2015;**38**(6):877–888. doi:10.5665/sleep.4732.
18. Adenekan B, *et al*. Sleep in America: role of racial/ethnic differences. *Sleep Med Rev*. 2013;**17**(4):255–262. doi:10.1016/j.smrv.2012.07.002.
19. Billings ME, *et al*. Physical and social environment relationship with sleep health and disorders. *Chest*. 2020;**157**(5):1304–1312.
20. Duncan DT, *et al*. *Neighborhoods and Health*. 2nd ed. New York, NY: Oxford University Press; 2018: xiv, 372 pages.

21. Galea S, *et al*. *Urban Health*. Oxford, UK; New York, NY: Oxford University Press; 2019: xv, 437 pages.
22. Roux AVD, *et al*. Neighborhoods and health. *Ann N Y Acad Sci*. 2010;**1186**:125–145.
23. Ross CE, *et al*. Neighborhood disadvantage, disorder, and health. *J Health Soc Behav*. 2001;**42**(3):258–276.
24. Mair C, *et al*. Are neighbourhood characteristics associated with depressive symptoms? A review of evidence. *J Epidemiol Commun Health*. 2008;**62**(11):940–946.
25. Brunner E, *et al*. Social organization, stress, and health. *Soc Determ Health*. 2006;**2**:17–43.
26. Hill TD, *et al*. Neighborhood disorder, sleep quality, and psychological distress: testing a model of structural amplification. *Health Place*. 2009;**15**(4):1006–1013. doi:10.1016/j.healthplace.2009.04.001.
27. Mirowsky J, *et al*. *Social Causes of Psychological Distress*. New York, NY: Routledge; 2017.
28. Ensel WM, *et al*. The life stress paradigm and psychological distress. *J Health Soc Behav*. 1991;**32**(4):321–341.
29. Castro-Diehl C, *et al*. Association of sleep duration and quality with alterations in the hypothalamic-pituitary adrenocortical axis: the multi-ethnic study of atherosclerosis (MESA). *J Clin Endocrinol Metab*. 2015;**100**(8):3149–3158.
30. Chen XL, *et al*. Associations of allostatic load with sleep apnea, insomnia, short sleep duration, and other sleep disturbances: findings from the National Health and Nutrition Examination Survey 2005 to 2008. *Ann Epidemiol*. 2014;**24**(8):612–619.
31. Mancuso M, *et al*. Oxidative stress biomarkers in patients with untreated obstructive sleep apnea syndrome. *Sleep Med*. 2012;**13**(6):632–636. doi:10.1016/j.sleep.2011.10.030.
32. Kim EJ, *et al*. The effect of psychosocial stress on sleep: a review of polysomnographic evidence. *Behav Sleep Med*. 2007;**5**(4):256–278. doi:10.1080/15402000701557383.
33. Johnson DA, *et al*. Connecting neighborhoods and sleep health. In: Duncan DT, *et al*. eds. *The Social Epidemiology of Sleep*. New York, NY: Oxford University Press; 2019:409.
34. Hale L, *et al*. Recent updates in the social and environmental determinants of sleep health. *Curr Sleep Med Rep*. 2015;**1**(4):212–217. doi:10.1007/s40675-015-0023-y.
35. Hunter JC, *et al*. The association of sleep with neighborhood physical and social environment. *Public Health*. 2018;**162**:126–134. doi:10.1016/j.puhe.2018.05.003.
36. Vézina-Im L-A, *et al*. Individual, social and environmental determinants of sleep among women: protocol for a systematic review and meta-analysis. *BMJ Open*. 2017;**7**(6):e016592. doi:10.1136/bmjopen-2017-016592.
37. Tomfohr-Madsen L, *et al*. Neighborhood socioeconomic status and child sleep duration: a systematic review and meta-analysis. *Sleep Health*. 2020;**6**(5):550–562. doi:10.1016/j.sleh.2020.02.012.
38. Buysse DJ. Sleep health: can we define it? Does it matter? *Sleep*. 2014;**37**(1):9–17. doi:10.5665/sleep.3298.
39. Wong D. The modifiable areal unit problem (MAUP). In: Fotheringham AS, *et al*., eds. *The SAGE Handbook of Spatial Analysis*. London, UK: SAGE; 2009: 105–123.
40. Sadeh A. The role and validity of actigraphy in sleep medicine: an update. *Sleep Med Rev*. 2011;**15**(4):259–267. doi:10.1016/j.smrv.2010.10.001.
41. de Souza L, *et al*. Further validation of actigraphy for sleep studies. *Sleep*. 2003;**26**(1):81–85. doi:10.1093/sleep/26.1.81.
42. Johnson DA, *et al*. The neighborhood social environment and objective measures of sleep in the multi-ethnic study of atherosclerosis. *Sleep*. 2017;**40**(1). doi:10.1093/sleep/zsw016.
43. Troxel WM, *et al*. Neighborhood disadvantage is associated with actigraphy-assessed sleep continuity and short sleep duration. *Sleep*. 2018;**41**(10). doi:10.1093/sleep/zsy140.
44. Troxel WM, *et al*. Broken windows, broken Zzs: poor housing and neighborhood conditions are associated with objective measures of sleep health. *J Urban Health*. 2020;**97**(2):230–238.
45. DeSantis A, *et al*. Is the association between neighborhood characteristics and sleep quality mediated by psychological distress? An analysis of perceived and objective measures of 2 Pittsburgh neighborhoods. *Sleep Health*. 2016;**2**(4):277–282. doi:10.1016/j.sleh.2016.08.001.
46. Steptoe A, *et al*. Positive affect, psychological well-being, and good sleep. *J Psychosom Res*. 2008;**64**(4):409–415. doi:10.1016/j.jpsychores.2007.11.008.
47. Lee H, *et al*. Mediation Analysis. *JAMA*. 2019;**321**(7):697–698. doi:10.1001/jama.2018.21973.
48. Dubowitz T, *et al*. A natural experiment opportunity in two low-income urban food desert communities: research design, community engagement methods, and baseline results. *Health Educ Behav*. 2015;**42**:87s–96s.
49. Thurman SM, *et al*. Individual differences in compliance and agreement for sleep logs and wrist actigraphy: a longitudinal study of naturalistic sleep in healthy adults. *PLoS One*. 2018;**13**(1):e0191883. doi:10.1371/journal.pone.0191883.
50. Ustinov Y, *et al*. Actigraphy reliability with normal sleepers. *Behav Sleep Med*. 2013;**11**(5):313–320. doi:10.1080/15402002.2012.688779.
51. Anchouche K, *et al*. Use of actigraphy (wearable digital sensors to monitor activity) in heart failure randomized clinical trials: a scoping review. *Can J Cardiol*. 2021;**37**(9):1438–1449.
52. Groenwold RH, *et al*. Dealing with missing outcome data in randomized trials and observational studies. *Am J Epidemiol*. 2012;**175**(3):210–217. doi:10.1093/aje/kwr302.
53. Pikora TJ, *et al*. Developing a reliable audit instrument to measure the physical environment for physical activity. *Am J Prev Med*. 2002;**23**(3):187–194. doi:10.1016/s0749-3797(02)00498-1.
54. Brownson RC, *et al*. Measuring the environment for friendliness toward physical activity: a comparison of the reliability of 3 questionnaires. *Am J Public Health*. 2004;**94**(3):473–483. doi:10.2105/ajph.94.3.473.
55. Caughy MO, *et al*. A brief observational measure for urban neighborhoods. *Health Place*. 2001;**7**(3):225–236. doi:10.1016/s1353-8292(01)00012-0.
56. Ghosh-Dastidar M, *et al*. An audit tool for longitudinal assessment of the health-related characteristics of urban neighborhoods: implementation methods and reliability results. *BMC Public Health*. 2020;**20**(1):1519.
57. Krippendorff K. Estimating the reliability, systematic error and random error of interval data. *Educ Psychol Meas*. 1970;**30**(1):61–70. doi:10.1177/001316447003000105.
58. Feinstein AR, *et al*. High agreement but low kappa: I. The problems of two paradoxes. *J Clin Epidemiol*. 1990;**43**(6):543–549. doi:10.1016/0895-4356(90)90158-l.
59. Cicchetti DV, *et al*. High agreement but low kappa: II. Resolving the paradoxes. *J Clin Epidemiol*. 1990;**43**(6):551–558. doi:10.1016/0895-4356(90)90159-m.
60. Cellini N, *et al*. Direct comparison of two actigraphy devices with polysomnographically recorded naps in healthy young adults. *Chronobiol Int*. 2013;**30**(5):691–698. doi:10.3109/07420528.2013.782312.
61. Rosenberger ME, *et al*. Twenty-four hours of sleep, sedentary behavior, and physical activity with nine wearable

devices. *Med Sci Sports Exerc*. 2016;**48**(3):457–465. doi:10.1249/MSS.0000000000000778.
62. Zinkhan M, *et al*. Agreement of different methods for assessing sleep characteristics: a comparison of two actigraphs, wrist and hip placement, and self-report with polysomnography. *Sleep Med*. 2014;**15**(9):1107–1114. doi:10.1016/j.sleep.2014.04.015.
63. Acebo C, *et al*. Estimating sleep patterns with activity monitoring in children and adolescents: how many nights are necessary for reliable measures? *Sleep*. 1999;**22**(1):95–103. doi:10.1093/sleep/22.1.95.
64. Cole RJ, *et al*. Automatic sleep/wake identification from wrist activity. *Sleep*. 1992;**15**(5):461–469. doi:10.1093/sleep/15.5.461.
65. Grandner M, *et al*. Sleep duration and hypertension: analysis of >700,000 adults by age and sex. *J Clin Sleep Med*. 2018;**14**(6):1031–1039. doi:10.5664/jcsm.7176.
66. Liu Y, *et al*. Sleep duration and chronic diseases among US adults age 45 years and older: evidence from the 2010 Behavioral Risk Factor Surveillance System. *Sleep*. 2013;**36**(10):1421–1427. doi:10.5665/sleep.3028.
67. Grandner MA, *et al*. Habitual sleep duration associated with self-reported and objectively determined cardiometabolic risk factors. *Sleep Med*. 2014;**15**(1):42–50. doi:10.1016/j.sleep.2013.09.012.
68. Kessler RC, *et al*. Screening for serious mental illness in the general population with the K6 screening scale: results from the WHO World Mental Health (WMH) survey initiative. *Int J Methods Psychiatr Res*. 2010;**19**(S1):4–22. doi:10.1002/mpr.310.
69. Hardy SE, *et al*. Ability to walk 1/4 mile predicts subsequent disability, mortality, and health care costs. *J Gen Intern Med*. 2011;**26**(2):130–135. doi:10.1007/s11606-010-1543-2.
70. Smith KR, *et al*. Walkability and body mass index: density, design, and new diversity measures. *Am J Prev Med*. 2008;**35**(3):237–244. doi:10.1016/j.amepre.2008.05.028.
71. Sampson RJ, *et al*. Systematic social observation of public spaces: a new look at disorder in urban neighborhoods. *Am J Sociol*. 1999;**105**(3):603–651. doi:10.1086/210356.
72. Sampson RJ, *et al*. Beyond social capital: spatial dynamics of collective efficacy for children. *Am Sociol Rev*. 1999;**64**(5):633–660.
73. Ross CE, *et al*. Disorder and decay: the concept and measurement of perceived neighborhood disorder. *Urban Aff Rev*. 1999;**34**(3):412–432. doi:10.1177/10780879922184004.
74. Vansteelandt S, *et al*. Revisiting g-estimation of the effect of a time-varying exposure subject to time-varying confounding. *Epidemiol Methods*. 2016;**5**(1):37–56.
75. Kwan M-P. The limits of the neighborhood effect: contextual uncertainties in geographic, environmental health, and social science research. *Ann Am Assoc Geogr*. 2018;**108**(6):1482–1490. doi:10.1080/24694452.2018.1453777.
76. Wodtke GT. Duration and timing of exposure to neighborhood poverty and the risk of adolescent parenthood. *Demography*. 2013;**50**(5):1765–1788. doi:10.1007/s13524-013-0219-z.
77. Dukes O, *et al*. A note on G-estimation of causal risk ratios. *Am J Epidemiol*. 2018;**187**(5):1079–1084. doi:10.1093/aje/kwx347.
78. Bind M-A, *et al*. Causal mediation analysis for longitudinal data with exogenous exposure. *Biostatistics*. 2016;**17**(1):122–134. doi:10.1093/biostatistics/kxv029.
79. VanderWeele TJ, *et al*. Mediation analysis with time varying exposures and mediators. *J R Stat Soc Series B Stat Methodol*. 2017;**79**(3):917–938.
80. Rudolph KE, *et al*. Causal mediation analysis with observational data: considerations and illustration examining mechanisms linking neighborhood poverty to adolescent substance use. *Am J Epidemiol*. 2019;**188**(3):598–608. doi:10.1093/aje/kwy248.
81. Kisbu-Sakarya Y, *et al*. Causal mediation analysis in the presence of post-treatment confounding variables: a Monte Carlo simulation study. *Front Psychol*. 2020;**11**:2067.
82. Hernán MA, *et al*. A structural approach to selection bias. *Epidemiology*. 2004;**15**(5):615–625.
83. Valeri L, *et al*. Mediation analysis allowing for exposure–mediator interactions and causal interpretation: theoretical assumptions and implementation with SAS and SPSS macros. *Psychol Methods*. 2013;**18**(2):137–150. doi:10.1037/a0035596.
84. Tingley D, *et al*. Mediation: R package for causal mediation analysis. *J Stat Soft*. 2014;**59**:1–38.
85. Vansteelandt S, *et al*. Revisiting g-estimation of the effect of a time-varying exposure subject to time-varying confounding. *Epidemiol Methods*. 2016;**5**(1):37–56.
86. Hale L, *et al*. Perceived neighborhood quality, sleep quality, and health status: evidence from the Survey of the Health of Wisconsin. *Soc Sci Med*. 2013;**79**:16–22.
87. Johnson SL, *et al*. Neighborhood violence and its association with mothers' health: assessing the relative importance of perceived safety and exposure to violence. *J Urban Health*. 2009;**86**(4):538–550. doi:10.1007/s11524-009-9345-8.
88. Roux AVD. Neighborhoods and health: what do we know? What should we do? *Am J Public Health*. 2016;**106**(3):430–431.
89. Curtis DS, *et al*. Habitual sleep as a contributor to racial differences in cardiometabolic risk. *Proc Natl Acad Sci USA*. 2017;**114**(33):8889–8894. doi:10.1073/pnas.1618167114.
90. Renauer BC. Is neighborhood policing related to informal social control? *Policing*. 2007;**03**(1):61–81.
91. Hirschfield A, *et al*. The effect of social cohesion on levels of recorded crime in disadvantaged areas. *Urban Stud*. 1997;**34**(8):1275–1295. doi:10.1080/0042098975637.
92. Sampson RJ. Crime in cities: the effects of formal and informal social control. *Crime Justice*. 1986;**8**:271–311. doi:10.1086/449125.
93. Sampson RJ. Linking the micro-and macrolevel dimensions of community social organization. *Social Forces*. 1991;**70**(1):43–64. doi:10.2307/2580061.
94. Oakes JM. The (mis)estimation of neighborhood effects: causal inference for a practicable social epidemiology. *Soc Sci Med*. 2004;**58**(10):1929–1952.
95. Andrews RM, *et al*. Insights into the cross-world Independence assumption of causal mediation analysis. *Epidemiology*. 2020;**32**(2):209–219. doi:10.1097/ede.0000000000001313.
96. Glymour MM, *et al*. When is baseline adjustment useful in analyses of change? An example with education and cognitive change. *Am J Epidemiol*. 2005;**162**(3):267–278. doi:10.1093/aje/kwi187.
97. Matthews SA. Spatial polygamy and the heterogeneity of place: studying people and place via egocentric methods. In: Burton L, *et al*., eds. *Communities, Neighborhoods, and Health: Expanding the Boundaries of Place*. New York, NY: Springer; 2011:35–55.
98. Van Dyck D, *et al*. Relationships between neighborhood walkability and adults' physical activity: how important is residential self-selection? *Health Place*. 2011;**17**(4):1011–1014. doi:10.1016/j.healthplace.2011.05.005.
99. Mujahid MS, *et al*. Assessing the measurement properties of neighborhood scales: from psychometrics to ecometrics. *Am J Epidemiol*. 2007;**165**(8):858–867. doi:10.1093/aje/kwm040.