Preventive Medicine Reports 32 (2023) 102131

Contents lists available at ScienceDirect

Preventive Medicine Reports

journal homepage: www.elsevier.com/locate/pmedr

Associations between observed neighborhood physical disorder and health behaviors, New Jersey behavioral risk factor Surveillance System 2011–2016

Jesse J. Plascak [a,b,*], Tatyana Desire-Brisard [c], Darren Mays [a,d], Brittney Keller-Hamilton [a,d], Andrew G. Rundle [e], Emma Rose [f], Electra D. Paskett [a,b], Stephen J. Mooney [g]

[a] Comprehensive Cancer Center, The Ohio State University, Columbus, OH, USA
[b] Division of Cancer Prevention and Control, Department of Internal Medicine, College of Medicine, The Ohio State University, Columbus, OH, USA
[c] School of Public Health, Rutgers University, Piscataway, NJ, USA
[d] Division of Medical Oncology, Department of Internal Medicine, College of Medicine, The Ohio State University, Columbus, OH, USA
[e] Department of Epidemiology, Mailman School of Public Health, Columbia University, New York, NY, USA
[f] Brigham Young University, Provo, UT, USA
[g] Department of Epidemiology, School of Public Health, University of Washington, Seattle, WA, USA

ARTICLE INFO

Keywords:
Observed neighborhood physical disorder
Tobacco use
Alcohol binging
Sugar-sweetened beverage consumption
Population-based surveillance

ABSTRACT

This study tested associations between observed neighborhood physical disorder and tobacco use, alcohol binging, and sugar-sweetened beverage consumption among a large population-based sample from an urban area of the United States. Individual-level data of this cross-sectional study were from adult respondents of the New Jersey Behavioral Risk Factor Surveillance System, 2011–2016 (n = 62,476). Zip code tabulation area-level observed neighborhood physical disorder were from virtual audits of 23,276 locations. Tobacco use (current cigarette smoking or chewing tobacco, snuff, or snus use), monthly binge drinking occasions (5+/4+ drinks per occasion among males/females), and monthly sugar-sweetened beverages consumed were self-reported. Logistic and negative binomial regression models were used to generate odds ratios, prevalence rate ratios (PRR), 95 % confidence intervals (CI) by levels of physical disorder. Compared to the lowest quartile, residence in the second (PRR: 1.16; 95 % CI: 1.03, 1.13), third (PRR: 1.24; 95 % CI: 1.10, 1.40), and fourth (highest) quartile of physical disorder (PRR: 1.24; 95 % CI: 1.10, 1.40) was associated with higher monthly sugar-sweetened beverage consumption. Associations involving tobacco use and alcohol binging were mixed. Observed neighborhood disorder might be associated with unhealthy behaviors, especially sugar-sweetened beverage consumption.

1. Introduction

Tobacco use, alcohol consumption, and poor diet are top ranking risk factors for chronic disease morbidity and mortality globally including in the United States (Collaborators, 2022; Ford et al., 2011; Islami et al., 2018). These health behaviors tend to co-occur within individuals and geographically cluster across places (Brazil, 2022; Mudryj et al., 2019). Identifying common drivers of multiple unhealthy behaviors is a key function of an effective public health response to the growing chronic disease burden.

Observed neighborhood physical disorder – visual indicators of disinvestment acting as neighborhood stressors – is one such factor (Branas et al., 2018; Raleigh and Galster, 2015; Sampson and Raudenbush, 2004). Neighborhood physical disorder has been gaining attention in the sociologic (Burt et al., 2022; O'Brien et al., 2022), epidemiologic (Keyes et al., 2012; Mayne et al., 2018; Messer et al., 2012; Meyers et al., 2013; Plascak et al., 2022), and urban revitalization (Branas et al., 2018) literatures as findings have suggested it may affect health through psychosocial and behavioral pathways. Several studies have reported associations between higher observed neighborhood physical disorder and

* Corresponding author at: Division of Cancer Prevention and Control, Department of Internal Medicine, College of Medicine, The Ohio State University, 1590 North High Street, Suite 525, Columbus, OH 43201, USA.
E-mail addresses: jesse.plascak@osumc.edu (J.J. Plascak), td418@scarletmail.rutgers.edu (T. Desire-Brisard), Darren.mays@osumc.edu (D. Mays), Brittney.keller-hamilton@osumc.edu (B. Keller-Hamilton), agr3@cumc.columbia.edu (A.G. Rundle), electra.paskett@osumc.edu (E.D. Paskett), sjm2186@u.washington.edu (S.J. Mooney).

https://doi.org/10.1016/j.pmedr.2023.102131
Received 15 November 2022; Received in revised form 26 January 2023; Accepted 6 February 2023
Available online 9 February 2023

greater tobacco smoking and alcohol consumption (Brown et al., 2014; Furr-Holden et al., 2011; Keyes et al., 2012; Mayne et al., 2018; Messer et al., 2012; Meyers et al., 2013). Fewer studies have tested associations between observed neighborhood physical disorder and diet, though one study reported no evidence of an association with weekly frequency of sugar sweetened beverage consumption (Mayne et al., 2018).

Despite this growing interest in observed neighborhood physical disorder, several important gaps remain. All studies of the effects of observed neighborhood physical disorder on health behaviors have been geographically limited to a few cities or counties preventing generalizability across large geographic areas and populations. Many studies have been conducted among select sub-populations – children and adolescents, pregnant people, women of childbearing age, minoritized racial-ethnic groups – (Furr-Holden et al., 2011; Keyes et al., 2012; Mayne et al., 2018; Meyers et al., 2013) and it is largely unknown whether observed neighborhood physical disorder is associated with health behaviors within a population-based, general-risk sample. Few studies have investigated associations with multiple health behaviors, including dietary factors, within the same sample (Mayne et al., 2018), which could inform potential mechanisms through which observed neighborhood physical disorder might impact health outcomes. A recent review of neighborhood disorder and health has highlighted the need for more studies that adjust for potential confounders (O'Brien et al., 2019), including socioeconomic factors and measures of the tobacco, alcohol, and the food environment (Maani et al., 2020).

Prior evidence suggests that exposure to higher neighborhood physical disorder might influence a physiologic stress response (Branas et al., 2018; O'Brien et al., 2019). Separate evidence suggest that tobacco use, alcohol consumption, and sugar-sweetened beverage consumption are a response to exposures of stress or distress (Park and Iacocca, 2014; Wiss et al., 2020). Thus, we are conceptualizing neighborhood physical disorder as a potential stressor that could influence individual-level variation in substance use and diet.

The purpose of this study was to address aforementioned gaps and investigate relationships between observed neighborhood physical disorder and health-related behaviors, adjusting for potentially influential covariates identified in previous literature (Maani et al., 2020; O'Brien et al., 2019). Specifically, we tested associations between physical disorder and current tobacco use, monthly alcohol binge drinking, and monthly sugar-sweetened beverage consumption adjusted for key individual- and neighborhood-level demographic, socioeconomic, and retailer environmental factors among a population-based sample of general-risk adults residing in a large urban area of the United States.

2. Methods

2.1. Data

2.1.1. Behavioral risk factor Surveillance System

All individual-level data were self-reported from the New Jersey Behavioral Risk Factor Surveillance System (NJBRFSS), an annual, cross-sectional, phone-based, state-administered questionnaire designed to assess major health behaviors and risks in the general population (Centers for Disease and Prevention, 2012). It uses a stratified, random digit dialing approach. Survey years 2011–2016 were included (sugar-sweetened beverage questions were only asked among random subsets of 2011–2014, 2016 survey respondents) (see Appendix for NJBRFSS details).

2.1.2. Individual-level outcomes

Tobacco use (current cigarette smoking or chewing tobacco, snuff, or snus use), monthly binge drinking occasions (5+ drinks per occasion among males, 4+ drinks per occasion among females), and average monthly number of sugar-sweetened beverages consumed were from NJBRFSS.

2.1.3. Individual-level covariates

We extracted age (18+ years), sex (male or female), race-ethnicity (non-Hispanic White; non-Hispanic Black/African American (AA); non-Hispanic Asian, no other racial identifier; non-Hispanic Asian Indian; non-Hispanic Chinese; non-Hispanic Filipino, Japanese, Korean, Vietnamese, other (hereafter, 'other Asian'); non-Hispanic Native Hawaiian, Guamanian/Chamorro, Samoan, other Pacific Islander (hereafter, 'NH/OPI'); non-Hispanic American Indian or Alaska Native (AI/AN); non-Hispanic other; non-Hispanic multiracial; Mexican, Mexican American, Chicano/a (hereafter, 'Mexican'); Puerto Rican; Cuban; Other Latinx), marital status (never married; widowed, divorced, separated; married or unmarried couple), educational attainment (<high school, high school diploma, attended college/technical school, completed college/technical school), household income (<$10,000, $10,000-$14,999, $15,000-$19,999, $20,000-$24,999, $25,000-$34,999, $35,000-$49,999, $50,000-$74,999, ≥$75,000), employment status (employed for wages or self-employed; homemaker, student, retired; unemployed), and zip code from survey data. The median dollar amount between income ranges was calculated and handled as a continuous variable in all analyses (<$10,000 and ≥$75,000 calculated as $5,000 and $100,000, respectively). Racial-ethnic categories were limited to non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, non-Hispanic NH/OPI, non-Hispanic AI/AN, non-Hispanic other, non-Hispanic multiracial, Hispanic/Latinx any racial identity in 2011 and 2012 because Hispanic/Latinx, Asian, and NH/OPI racial-ethnic subcategories were unavailable then.

2.1.4. Observed neighborhood physical disorder

Observed physical disorder was estimated from neighborhood virtual audits of 23,276 urban streetscapes across New Jersey (census tract Rural-Urban Commuting Code = 'Metropolitan core') (Plascak et al., 2020a; Plascak et al., 2020b). We used the virtual auditing platform CANVAS which interfaces with Google Streetview streetscapes (Bader et al., 2015). Four trained raters followed the 'drop-and-spin' protocol to assess the 360° view of each streetscape for six indicators of physical disorder: presence of graffiti, litter, boarded up or burned buildings, the number of large dumpsters, building conditions, and yard conditions (Plascak et al., 2020b). Graffiti, litter, and boarded up or burned buildings were all dichotomous yes/no variables. Number of dumpsters were recorded as "none", "1–2", or ">2", while the building and yard conditions were both coded as "very good", "moderate", "fair", or "poor". Item ratings were combined into a single physical disorder score for each streetscape assessed (Plascak et al., 2020a). Universal kriging, a spatial modeling technique, allowed prediction of physical disorder at any urban location across the study region (Mooney et al., 2018). As audits were limited to urban census tracts, we limited kriging predictions to portions of zip code tabulation areas (ZCTA) that overlapped urban census tracts (535 of 595, 90 % of ZCTAs). ZCTA-level physical disorder values were calculated from kriging models in a three-step process: 1) generate 30 spatially random points within each urban ZCTA (n = 16,050 total points); 2) predict physical disorder at each location; 3) average the 30 estimates within each ZCTA (intraclass-correlation coefficient of physical disorder = 0.77). These averages were linked to BRFSS data through participant-reported zip code. Physical disorder was further analyzed as quartiles of the 535 ZCTAs (approximately 134 ZCTAs per quartile). Audit item rater agreement reliability (e.g., maximum test–retest ≥ 'substantial agreement'), physical disorder internal consistency reliability (0.965), kriging model prediction accuracy (e.g., all audit item's area under the curve ≥ 0.849), and audit sampling and protocol details have been previously published (Plascak et al., 2020b; Plascak et al., 2022; Plascak et al., 2020c).

2.1.5. Social deprivation Index

We calculated the social deprivation indices (SDI) for each ZCTA from seven socioeconomic variables derived from annual, five-year American Community Survey data – percent of the population (ages

25 years or more) with less than a high school diploma ('% <high school'), percent of the population with household income <100 % of the federal poverty level ('% <federal poverty level'), percent of the civilian labor force that are not employed ('% non-employed'), percent of housing units that are renter occupied ('% rental'), percent of occupied housing units that have more than one person per a room ('% crowded'), percent of housing units with no vehicle availability ('% no vehicle'), and percent of families that are headed by one adult and which contain children ('% single parent') (Butler et al., 2013). Following Butler, Petterson et al., 2013, we calculated annual SDI scores using ZCTA population-weighted factor analysis of the seven variables. Annual BRFSS data were linked to SDI data by the last year of ACS data; SDI from ACS 2012–2016 data linked to 2016 BRFSS data, ACS 2007–2011 linked to 2011 BRFSS data, etc. ZCTA population density (persons per square mile) was quantified using the annual population data and geographic information system-calculated ZCTA area.

2.1.6. Food and substance environment

We used ZCTA-level food, alcohol, and tobacco establishment data from the 2011–2016, annual County Business Patterns series (Bureau et al., 2020). Following previous literature on food swamps (Cooksey-Stowers et al., 2017), food environment was characterized from five NAICS categories: 'limited-service restaurants' (fast food), 'convenience stores', 'Cafeterias, grill buffets, and buffets', 'Snack and nonalcoholic beverage bars', and 'grocery stores or supermarkets'. The percentage of unhealthy food options – 100 × (limited-service restaurants + convenience stores + cafeterias, grill buffets, and buffets + snack and nonalcoholic beverage bars) ÷ (limited-service restaurants + convenience stores + cafeterias, grill buffets, and buffets + snack and nonalcoholic beverage bars + grocery stores or supermarkets) – was calculated for each ZCTA (Cooksey-Stowers et al., 2017). A six-category food environment variable was created based on this proportion: only grocery stores (numerator = 0), only unhealthy stores (no grocery stores or supermarkets), no food stores (numerator and denominator = 0), and three food swamp tertiles.

Number of 'Beer, wine, and liquor stores' (off-premise) and 'Drinking places (alcoholic beverages)' (on-premise) were used to characterize the alcohol environment and number of 'Tobacco stores' stores was used to characterize the tobacco environment. Establishment density (per 100,000 persons, using population data above) was calculated for alcohol and tobacco environment variables. Alcohol and tobacco environment variables were each analyzed as categories: none, <median, and ≥median, where median values were calculated from distributions of non-zero density values.

2.2. Statistical analysis

Annual survey data from respondents residing in urban zip codes were pooled across all years to increase sample size (n = 63418). Variable missingness was as follows: income (7252, 11.4 %), alcohol binging (3462, 5.4 %), tobacco use (1644, 2.6 %), SDI (1046, 1.6 %), population density (1022, 1.6 %), race-ethnicity (942, 1.5 %), marital status (266, 0.4 %), employment status (232, 0.4 %), and education (124, 0.2 %). Respondent data from urban zip codes and who were administered the sugar-sweetened beverage consumption module (19863) had similar variable missingness including 419 (2.1 %) missing sugar-sweetened beverage and 294 (1.5 %) missing race-ethnicity responses. We conducted missing data imputation analyses, imputing 25 datasets using multiple imputation by chained equations and imputing all variables with missing data except for race-ethnicity by dataset (larger dataset used to test associations with alcohol binging and tobacco use and smaller dataset containing sugar-sweetened beverage responses) (Rubin, 2004). We did not impute race-ethnicity because of the small percentage missing, larger subgroup sample sizes, and to respect respondent desires to withhold their racial-ethnic identity (Randall et al., 2021). Regression results were combined according to Rubin's rules (Rubin, 2004).

A map was created to describe the geographic distribution of estimated, ZCTA-level physical disorder (Fig. 1). Frequencies and percentages were used to summarize distributions of physical disorder by covariates. Frequencies and percentages (tobacco use) and means and standard errors (S.E.) (monthly alcohol binging occasions and monthly sugar-sweetened beverage consumption) were calculated to summarize distributions of health behaviors by covariate levels. Separate mixed effects regression models accounting for nesting of respondents in ZCTAs and survey design weights were built for each health behavior; a logistic regression model for tobacco use and negative binomial models for monthly alcohol binging occasions and monthly sugar-sweetened beverage consumption. Each model included a random intercept for ZCTA. Two general modelling frameworks were built for each health behavior based on covariate relationships summarized in exploratory analyses: Model 1 included all covariates except for food and substance environment covariates and Model 2 included all covariates. As a sensitivity analysis we modeled monthly alcohol binging occasions using single-level, zero-inflated negative binomial regression (86.0 % respondents with '0′ binging occasions) by including all covariates in both the zero-inflated and count process model portions. All descriptive and inferential analyses were survey-weighted to account for complex survey design. Post-hoc analyses include: 1) area-level correlation matrix (see Appendix), 2) test for ordinal trend of associations involving physical disorder, and 3) minimally adjusted models. ArcGIS v10.8 and SAS v9.4 were used for geographic and statistical analyses, respectively. Physical disorder data were collected January 2018–June 2019, streetscape dates ranged August 2007–September 2018, and measurement properties analyzed through July 2020. The Ohio State University Institutional Review Board approved this study protocol.

3. Results

3.1. Geographic distribution of neighborhood physical disorder

ZCTA physical disorder across urban areas was highest around populous cities, with ZCTAs adjacent to populous cities having some of the lowest physical disorder values (Fig. 1).

Distributions of numerous demographic, socioeconomic, and ZCTA factors among the 62,476 respondents appear to vary substantially across quartiles of ZCTA physical disorder (Table 1).

3.2. Sample characteristics by levels of neighborhood physical disorder

Approximately 25 % of respondents residing in the highest quartile of physical disorder self-identify as non-Hispanic Black/AA compared to 32.2 % self-identifying as non-Hispanic White. Other notable distributions of factors among those residing in the highest quartile of physical disorder include: 64.4 % have incomes below the median; 91.7 % are residing in higher social deprivation ZCTAs; and 77.3 %% are residing in ZCTAs with higher density of off-premise alcohol retailers (see Appendix for distributions among sugar-sweetened beverage respondents).

3.3. Sample characteristics by levels of tobacco use, alcohol binging, and sugar-sweetened beverage consumption

Current tobacco use, average monthly alcohol binge drinking occasions, and average monthly sugar-sweetened beverage consumption was 16.9 %, 0.6, and 16.6 respectively. Tobacco use varied across physical disorder quartiles: 13.3 %, 16.6 %, 19.4 % and 19.1 % from the lowest to highest quartile respectively (Table 2). Similarly average monthly sugar-sweetened beverage consumption was 12.04 in ZCTAs of lowest physical disorder and 25.14 in ZCTAs of highest physical disorder. Notable additional self-identified groupings reporting higher current tobacco use compared to the overall sample include: younger than 55 years of age (19.3 %), males (19.5 %), never married (23.2 %), non-Hispanic Black/

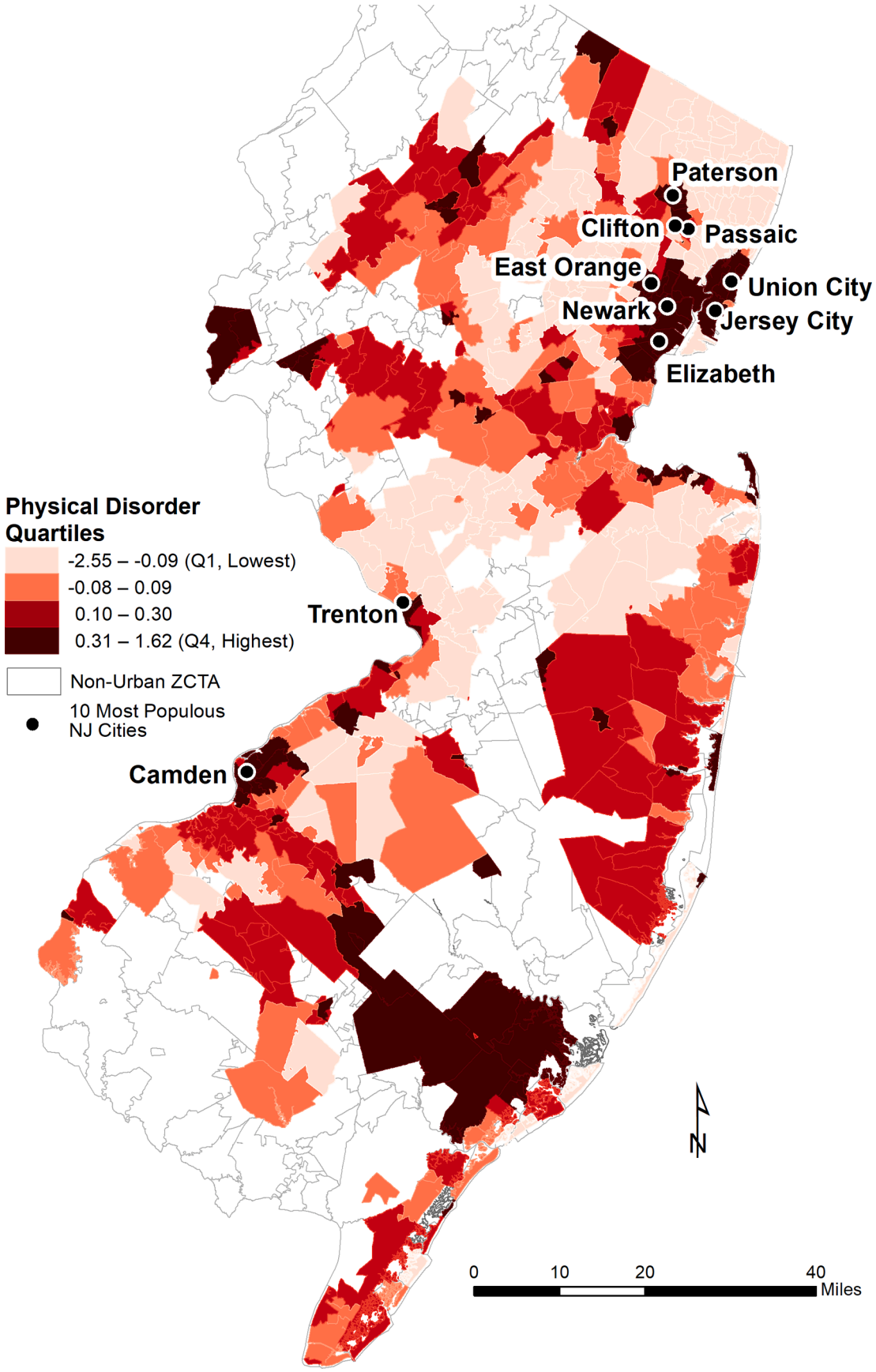

Fig. 1. Observed neighborhood physical disorder within New Jersey urban zip codes.

Table 1
Demographic and socioeconomic factors by physical disorder, NJBRFSS 2011–2016, n = 62,476.

	Physical Disorder, N (%)[1] Q1 (Lowest)	Q2	Q3	Q4 (Highest)
Overall	15,595 (30.1)	15,673 (22.9)	15,570 (23.5)	15,638 (23.6)
Age (median)				
<55 years	7328 (60.3)	7379 (63.1)	7218 (62.7)	8583 (69.8)
≥55 years	8267 (39.7)	8294 (36.9)	8352 (37.3)	7055 (30.2)
Sex				
Male	6721 (48.6)	6588 (48.9)	6342 (46.8)	6209 (48.8)
Female	8874 (51.4)	9085 (51.1)	9228 (53.2)	9429 (51.2)
Marital status				
Married/unmarried couple	9425 (61.5)	8822 (58.2)	8392 (56.9)	6700 (44.7)
Separated/divorced/ widowed	3840 (16.0)	4382 (17.1)	4605 (19.2)	4714 (20.2)
Never married	2280 (22.2)	2409 (24.3)	2521 (23.6)	4152 (34.7)
Race-ethnicity				
Non-Hispanic White	12,612 (70.5)	12,365 (69.2)	11,965 (65.0)	6598 (32.2)
Non-Hispanic Black/ AA	743 (5.8)	1247 (10.0)	1466 (11.2)	4152 (25.1)
Non-Hispanic AI/AN	52 (0.4)	75 (0.4)	73 (0.4)	84 (0.5)
Non-Hispanic Asian	367 (4.2)	282 (2.9)	179 (2.1)	272 (2.0)
Non-Hispanic Asian Indian[1, 2 and 3]	274 (3.9)	209 (3.4)	149 (2.7)	150 (1.9)
Non-Hispanic Chinese[3]	96 (1.4)	43 (0.7)	49 (0.7)	30 (0.3)
Non-Hispanic Other Asian[3]	132 (2.4)	77 (1.2)	58 (1.1)	100 (1.2)
Non-Hispanic NH/OPI[3]	20 (0.1)	19 (0.2)	20 (0.1)	44 (0.3)
Non-Hispanic Multiracial	112 (0.8)	121 (0.7)	112 (0.9)	135 (0.8)
Non-Hispanic Other	126 (0.8)	120 (0.7)	120 (0.7)	181 (0.8)
Hispanic/Latinx	425 (2.9)	414 (3.4)	519 (5.1)	1613 (11.3)
Mexican[3]	69 (0.7)	102 (1.4)	155 (2.2)	160 (1.9)
Puerto Rican[3]	177 (1.8)	258 (2.0)	246 (2.3)	607 (5.2)
Cuban[3]	48 (0.3)	29 (0.3)	41 (0.3)	155 (1.3)
Other Hispanic/Latinx[3]	342 (4.1)	312 (3.6)	418 (5.2)	1357 (15.1)
Education				
<High school	520 (6.7)	786 (8.2)	1080 (12.6)	2084 (22.0)
High school diploma or equivalent	3076 (23.4)	4088 (28.6)	4770 (33.5)	4941 (33.0)
Some college or technical school	3297 (24.1)	3908 (27.9)	4055 (27.3)	3834 (24.2)
≥College or technical school	8677 (45.5)	6866 (35.1)	5646 (26.4)	4739 (20.6)
Income (median)[2]				
<$62,499.50	4100 (30.1)	5413 (37.2)	6245 (45.7)	8444 (64.4)
≥$62,499.50	9336 (69.9)	8105 (62.8)	7183 (54.3)	5067 (35.6)
Employment status				
Out of work/unable to work				
Student/homemaker/ retired	1381 (9.3)	1781 (11.8)	2041 (13.2)	2953 (18.9)
Employed	5153 (29.2)	5202 (26.9)	5248 (28.1)	4368 (22.6)
Survey Year	9012 (61.2)	8644 (61)	8225 (58.5)	8251 (57.9)
2011				
2012	3212 (16.5)	3027 (16.9)	3033 (16.5)	3343 (16.3)
2013	3345 (16.9)	3114 (16.6)	3194 (17.2)	3396 (16.6)
2014		2775 (17)	2715 (16)	2731 (17.5)
2015	2544 (16.3)	2673 (16.9)	2595 (16.3)	2566 (16.7)
2016	1520 (16.2)	1581 (15.9)	1560 (16.7)	1459 (16.6)
Social Deprivation Index (median)				
<31	12,243 (77.6)	8864 (62.3)	7855 (45.1)	1652 (8.3)
≥31	3283 (22.4)	6373 (37.7)	7685 (54.8)	13,489 (91.7)
Population Density (median)				
<869.1 persons per mile	8576 (47.5)	9349 (45.2)	9363 (45.8)	3472 (13.6)
≥869.1 persons per mile	6956 (51.7)	5889 (52.4)	6177 (54.1)	11,672 (84.3)
Food Environment				
No unhealthy stores/ Only grocery	27 (0.2)	12 (0.1)	64 (0.4)	0 (0.0)
Food swamp T1 (Low)	2492 (16.1)	2569 (15.5)	3959 (24.2)	10,313 (71.5)
Food swamp T2 (Middle)	4943 (32.4)	5631 (35.8)	5574 (40.4)	3173 (16.9)
Food swamp T3 (High)	7042 (45.8)	6536 (44.7)	4204 (27.2)	1743 (9.5)
Only unhealthy stores/ No grocery	969 (4.9)	917 (3.9)	1640 (7.4)	325 (1.8)
No food stores	122 (0.6)	8 (0.0)	129 (0.4)	84 (0.3)
Off-premises Alcohol Density				
None	1250 (6.9)	1285 (5.0)	1162 (4.8)	443 (3.3)
<18.1 premises per 100,000 persons	9119 (58.7)	8626 (55.3)	7847 (54.9)	3486 (19.4)
≥18.1 premises per 100,000 persons	5221 (34.4)	5761 (39.7)	6545 (40.3)	11,709 (77.3)
On-premises Alcohol Density				
None	6455 (38.0)	5160 (26.0)	4566 (24.3)	1303 (8.6)
<12.3 premises per 100,000 persons	6204 (44.2)	5626 (42.2)	5508 (40.5)	5023 (31.0)
≥12.3 premises per 100,000 persons	2931 (17.8)	4886 (31.8)	5480 (35.2)	9312 (60.3)
Tobacco Retailer Density				
None	11,721 (72.9)	10,698 (65.6)	10,282 (53.7)	10,902 (66.8)
<3.7 retailers per 100,000 persons	2365 (16.0)	2067 (16.0)	2486 (25.1)	2829 (20.4)
≥3.7 retailers per 100,000 persons	1504 (11.1)	2907 (18.3)	2786 (21.1)	1907 (12.8)

[1] Percentage calculations account for complex survey design weights.
[2] 'Median' indicates that variables were dichotomized using median as a cutpoint.
[3] More detailed race-ethnicity responses in 2013–2016 questionnaires.

AA (21.3 %), Puerto Rican (22.1 %), less than a HS diploma (24.3 %), income less than $62,499.50 (21.8 %), and out of work/unable to work (30.1 %). Higher sugar-sweetened beverage consumption follow similar patterns. Notable higher monthly alcohol binging occasions compared to the overall sample by self-identified groupings included: younger than 55 years of age (0.78), males (0.86), never married (0.99), non-Hispanic, White (0.71), income at least $62,499.50 (0.73), and the employed (0.71).

3.4. Associations between neighborhood physical disorder and tobacco use, alcohol binging, and sugar-sweetened beverage consumption

For all three outcomes adjustment for ZCTA-level food, alcohol, and

Table 2
Physical disorder, demographic, socioeconomic, and food / substance environmental factors by current tobacco use, monthly alcohol binge drinking occasions, and monthly sugar-sweetened beverage consumption, NJBRFSS 2011–2016, n = 62,476[1].

	Tobacco Use N (%)[2]	Alcohol Binging Occasions	Sugar-sweetened Beverages
	Yes	Mean (S.E.)[2]	Mean (S.E.) [2]
Overall	9464 (16.9)	0.60 (0.02)	16.60 (0.46)
Physical disorder (quartiles)			
Q1 (Lowest)	1765 (13.3)	0.57 (0.04)	12.04 (0.57)
Q2	2322 (16.6)	0.64 (0.04)	14.7 (0.69)
Q3	2618 (19.4)	0.59 (0.03)	16.01 (0.71)
Q4 (Highest)	2759 (19.1)	0.63 (0.03)	25.14 (1.42)
Age (median)[3]			
<55 years	5630 (19.3)	0.78 (0.03)	20.39 (0.67)
≥55 years	3834 (12.6)	0.3 (0.02)	10.64 (0.41)
Sex			
Male	4334 (19.5)	0.86 (0.03)	19.49 (0.75)
Female	5130 (14.4)	0.37 (0.01)	13.95 (0.48)
Marital status			
Married/unmarried couple	3918 (13.1)	0.49 (0.02)	12.96 (0.4)
Separated/divorced/ widowed	3057 (19.4)	0.42 (0.03)	14.13 (0.59)
Never married	2464 (23.2)	0.99 (0.05)	27.2 (1.46)
Race-ethnicity			
Non-Hispanic White	6425 (17.5)	0.71 (0.03)	13.62 (0.41)
Non-Hispanic Black/AA	1454 (21.3)	0.47 (0.04)	29.01 (2.37)
Non-Hispanic AI/AN	61 (21.3)	0.42 (0.19)	17.13 (5.74)
Non-Hispanic Asian	96 (9.7)	0.24 (0.05)	8.87 (1.28)
Non-Hispanic Asian Indian[4]	76 (9)	0.15 (0.05)	7.02 (1)
Non-Hispanic Chinese[4]	15 (4.9)	0.24 (0.07)	10.83 (1.97)
Non-Hispanic Other Asian[4]	46 (13.1)	0.71 (0.25)	13.92 (4.67)
Non-Hispanic NH/OPI[4]	20 (21)	0.82 (0.27)	24.78 (8.14)
Non-Hispanic Multiracial	103 (18.4)	0.47 (0.1)	18.46 (7.16)
Non-Hispanic Other	100 (17.4)	0.31 (0.16)	8.97 (1.7)
Hispanic/Latinx	463 (15.8)	0.55 (0.06)	26.34 (2.23)
Mexican[4]	50 (11.6)	0.44 (0.07)	22.38 (3.11)
Puerto Rican[4]	260 (22.1)	0.58 (0.12)	21.93 (2.63)
Cuban[4]	37 (15.7)	0.64 (0.22)	14.45 (3.63)
Other Hispanic/Latinx[4]	258 (11.5)	0.41 (0.03)	19.79 (1.45)
Education			
<High school	1045 (24.3)	0.48 (0.05)	24.34 (1.65)
High school diploma or equivalent	3476 (22.5)	0.68 (0.04)	20.88 (0.78)
Some college or technical school	2655 (17.2)	0.69 (0.03)	17.38 (1.11)
≥College or technical school	2273 (8.9)	0.52 (0.02)	9.48 (0.39)
Income (median)[3]			
<$62,499.50	4887 (21.8)	0.51 (0.02)	22.1 (0.95)
≥$62,499.50	3487 (13.5)	0.73 (0.03)	11.88 (0.41)
Employment status			
Out of work/unable to work	2270 (30.1)	0.5 (0.04)	24.01 (1.29)
		0.42 (0.03)	12.32 (0.53)
Student/homemaker/ retired	2043 (10.4)		
Employed	5118 (16.9)	0.71 (0.02)	16.86 (0.64)
Survey Year			
2011	1989 (18)	0.65 (0.04)	15.11 (0.86)
2012	2024 (18.1)	0.61 (0.03)	18.83 (0.95)
2013	1743 (17.1)	0.57 (0.03)	17.26 (0.86)
2014	1516 (16.9)	0.61 (0.03)	16.83 (0.84)
2015	1307 (14.7)	0.56 (0.05)	NA
2016	885 (16.3)	0.64 (0.07)	15.9 (0.86)
Social Deprivation Index (median)[3]			
Low	3777 (14.7)	0.63 (0.03)	13.1 (0.47)
High	5557 (19.1)	0.58 (0.02)	20.27 (0.76)
Population Density (median)[3]			
Low	4485 (16.8)	0.62 (0.02)	14.46 (0.51)
High	4852 (17)	0.6 (0.03)	18.09 (0.66)
Food Environment			
No unhealthy stores/ Only grocery	18 (22.1)	0.5 (0.15)	8.78 (2.5)
Food swamp T1 (Low)	3313 (18.4)	0.61 (0.03)	21.87 (1.11)
Food swamp T2 (Middle)	2845 (16.5)	0.61 (0.03)	14.31 (0.62)
Food swamp T3 (High)	2683 (15.7)	0.6 (0.03)	14.81 (0.63)
Only unhealthy stores/ No grocery	560 (16.7)	0.62 (0.07)	12.67 (1.09)
No food stores	45 (13.7)	0.44 (0.13)	10.66 (2.63)
Off-premises Alcohol Density			
None	559 (17.2)	0.53 (0.05)	16.4 (1.7)
<18.1 premises per 100,000 persons	4044 (15.6)	0.59 (0.02)	13.97 (0.48)
≥18.1 premises per 100,000 persons	4857 (18)	0.63 (0.03)	19.32 (0.78)
On-premises Alcohol Density			
None	2238 (14.9)	0.59 (0.04)	13.78 (0.74)
<12.3 premises per 100,000 persons	3291 (16.2)	0.56 (0.03)	15.79 (0.57)
≥12.3 premises per 100,000 persons	3931 (19)	0.67 (0.03)	19.67 (0.94)
Tobacco Retailer Density			
None	6579 (17)	0.62 (0.02)	16.59 (0.58)
<3.7 retailers per 100,000 persons	1427 (16.3)	0.53 (0.03)	17.24 (0.91)
≥3.7 retailers per 100,000 persons	1454 (16.7)	0.65 (0.04)	15.78 (0.94)

[1] n = 19,569 among respondents of sugar-sweetened beverage questions.
[2] Percentage, mean, and standard deviation (S.E.) calculations account for complex survey design weights.
[3] 'Median' indicates that variables were dichotomized using median as a cutpoint.
[4] More detailed race-ethnicity responses in 2013–2016 questionnaires.

tobacco environment resulted in nearly identical associations as the model that excluded these covariates and so we focus on results of the final model (Table 3, Model 4). Adjusting for all covariates, residence in ZCTAs of the third quartile of physical disorder (second highest) was associated with odds of tobacco use that was 1.18 (95 % CI: 1.04, 1.59)

Table 3
Associations between current tobacco use, monthly alcohol binge drinking occasions, and monthly sugar-sweetened beverage consumption by levels of physical disorder NJBRFSS 2011–2016, n = 62,476[1].

	Effect estimate[2,3] (95 % CI)			
	Model 1	Model 2	Model 3	Model 4
Current tobacco use				
Physical disorder (quartiles)				
Q1 (Lowest)	1.00	1.00	1.00	1.00
Q2	1.26 (1.10,1.44)	1.10 (0.97,1.23)	1.07 (0.95,1.2)	1.06 (0.94,1.2)
Q3	1.50 (1.31,1.70)	1.23 (1.10,1.38)	1.18 (1.04,1.32)	1.17 (1.04,1.32)
Q4 (Highest)	1.54 (1.33,1.78)	1.13 (1.00,1.28)	1.06 (0.92,1.23)	1.06 (0.91,1.23)
p-value for ordinal trend[4]				0.187
Alcohol binging occasions				
Physical disorder (quartiles)				
Q1 (Lowest)	1.00	1.00	1.00	1.00
Q2	1.32 (1.12,1.55)	1.31 (1.11,1.53)	1.25 (1.07,1.47)	1.23 (1.05,1.44)
Q3	1.15 (0.98,1.36)	1.14 (0.97,1.34)	1.04 (0.88,1.23)	1.03 (0.87,1.21)
Q4 (Highest)	1.37 (1.15,1.63)	1.39 (1.17,1.66)	1.16 (0.94,1.43)	1.14 (0.93,1.41)
p-value for ordinal trend[4]				0.356
Sugar sweetened beverages consumed				
Physical disorder (quartiles)				
Q1 (Lowest)	1.00	1.00	1.00	1.00
Q2	1.18 (1.03,1.35)	1.19 (1.06,1.34)	1.17 (1.04,1.32)	1.16 (1.03,1.30)
Q3	1.35 (1.18,1.55)	1.27 (1.13,1.43)	1.22 (1.08,1.38)	1.24 (1.10,1.40)
Q4 (Highest)	1.62 (1.40,1.88)	1.45 (1.28,1.65)	1.37 (1.18,1.60)	1.37 (1.17,1.59)
p-value for ordinal trend[4]				<0.0001

[1] n = 19,569 among respondents of sugar-sweetened beverage questions.
[2] From logistic (odds ratios of tobacco use) or negative binomial (prevalence rate ratios of alcohol and beverage consumption) models accounting for the complex survey design weights and clustering of respondents within zip code tabulation areas via random intercepts.
[3] Model 1 includes age, sex, marital status, race-ethnicity, survey year; model 2 includes model 1 + education, income, employment status; model 3 includes model 2 + population density, social deprivation index; model 4 includes model 3 + + food environment, off-premises alcohol density, on-premises bar density, and tobacco retailer density.
[4] From test of ordinal trend where all observations within each quartile of physical disorder were set to the median value and models re-ran to report the *t*-test corresponding to this physical disorder variable regression coefficient.

times that of those in the lowest physical disorder quartile (Table 3). There were no other associations between other levels of physical disorder and tobacco use. Adjusting for all covariates, residence in ZCTAs of the second quartile of physical disorder (second lowest) was associated with a rate of monthly alcohol binging occasions that was 1.23 (95 % CI: 1.05, 1.44) times that of those in the lowest physical disorder quartile (Table 3). There were no other associations between other levels of physical disorder and alcohol binging. Adjusting for all covariates, residence in ZCTAs of the highest physical disorder quartile was associated with a rate of monthly sugar-sweetened beverage consumption that was 1.37 (95 % CI: 1.17, 1.59) times that of those in the lowest physical disorder quartile. Compared to the lowest quartile, residence in the second (PRR: 1.16; 95 % CI: 1.03, 1.13) and third (PRR: 1.24; 95 % CI: 1.10, 1.40) physical disorder quartiles was also associated with higher monthly sugar-sweetened beverage consumption. (see Appendix for full model results).

3.5. Sensitivity analyses

Results of sensitivity analyses that modeled monthly alcohol binging occasions according to a zero-inflated negative binomial distribution provide a slightly different interpretation compared to main analyses. In fully adjusted models there were no associations between physical disorder and number of alcohol binging occasions among those who report at least one binging occasion; that is, physical disorder was not associated with the rate of binging among those who binged in the past month. However, compared to the lowest quartile of ZCTA physical disorder, odds of reporting any binge drinking for those residing in the second lowest (Q2), second highest (Q3), and highest quartile (Q4) of ZCTA physical disorder was 1.42 (95 % CI: 1.23, 1.64), 1.17 (95 % CI: 1.04, 1.31), and 1.24 (95 % CI: 1.11, 1.39); residence in higher physical disorder ZCTAs was associated with greater odds of any binge drinking in the past month.

4. Discussion

This study found evidence for associations between observed neighborhood physical disorder and major health behaviors. Despite a clear pattern of higher percentages of tobacco use among those residing in higher physical disorder areas, adjusting for demographic and socioeconomic covariates largely accounted for this trend. There was evidence for associations between higher physical disorder alcohol binging (versus none). The most consistent results indicated a linear trend between higher physical disorder and increased frequency of sugar-sweetened beverage consumption.

Neighborhood physical disorder is an indicator of disinvestment that might impact health behaviors through psychosocial stress pathways (Burt et al., 2022; Keyes et al., 2012; Mayne et al., 2018; O'Brien et al., 2019). Such explanations posit that residents of higher physical disorder areas perceive this higher disorder (O'Brien et al., 2019), which triggers neuroendocrine pathways involved in maladaptive stress responses potentially leading to engagement in unhealthy behaviors (Agorastos and Chrousos, 2022; McEwen, 1998). Under this psychosocial framework, variability in associations involving tobacco use, alcohol binging, or sugar-sweetened beverage consumption found in this study could be due to numerous health behavior-specific reasons including: physiologic mechanisms and temporal dynamics, product affordability, and numerous unmeasured factors (e.g., alternative stress-reducing behaviors, addictiveness and timing of exposure, etc.). Targeted marketing in disinvested areas could offer alternative explanations (Isgor et al., 2016).

4.1. Comparison to previous literature

In contrast to findings of this study, other studies have reported associations between higher observed neighborhood physical disorder and tobacco use. (Brown et al., 2014; Furr-Holden et al., 2011; Keyes et al., 2012; Mayne et al., 2018; Messer et al., 2012) For example, a cross-sectional study of young adults residing in Baltimore City, Maryland found evidence that higher observed neighborhood disorder was associated with 17 % higher odds of past month tobacco use.(Brown et al., 2014) Similarly, studies of observed neighborhood physical disorder and alcohol consumption tend to report positive associations.(Chauhan et al., 2016; Keyes et al., 2012) The only known study to investigate and report no association between observed neighborhood physical disorder and sugar-sweetened beverage consumption was among women of child-bearing age residing in Chicago, Illinois (Mayne et al., 2018).

Possible explanations for the divergent findings of the current study may be related to use of ZCTAs to approximate neighborhoods or

general similarities of most previous investigations. Previous studies typically measured disorder at smaller units such as block face, encompassed smaller and potentially unique geographic regions (e.g., New York City, Baltimore City, etc.), focused on select sub-populations (e.g., young adults, people giving birth, etc.), and few studies adjusted for both individual- and neighborhood-level socioeconomic factors. (Keyes et al., 2012; Mayne et al., 2018) Adjustment for potential confounders could be especially critical because numerous studies, including the current study, report how associations between physical disorder and health behaviors were sharply attenuated with adjustment for socioeconomic factors. Socioeconomic factors might be independently related to levels of neighborhood physical disorder, health behaviors, and selective residential mobility, underscoring the importance of measuring and controlling for such factors, as noted in a recent review (O'Brien et al., 2019). Despite growing attention on the 'commercial determinants of health' (Maani et al., 2020), adjustment for measures of the food, tobacco, and alcohol retailer environments had little impact on associations of this study. However, the interplay of and adjustment for area-level socioeconomic factors and population density along with cross-sectional design of this study makes it difficult to draw firm conclusions about the role of these retailer environment factors on health behaviors.

4.2. Strengths and limitations

The large, population-based average-risk sample of adults; geographically large study area; adjustment for numerous individual- and area-level covariates; and use of reliable observed physical disorder measures are strengths of this study. Despite these strengths, the cross-sectional design; lack of other tobacco combustibles (e.g., cigars, cigarellos, etc.); use of ZCTAs as convenience approximations of neighborhoods; potential for under-reporting of unhealthy behaviors; unmeasured confounders (social cohesion, residential mobility); potential study area distinctions (zoning policies, tobacco and alcohol sale restrictions, etc.); and partial temporal mismatch of physical disorder measures and health behaviors are limitations that future studies should address.

5. Conclusion

Built environment physical disorder is modifiable, potentially acts as a neighborhood stressor, and has growing evidence for a role in health behaviors and outcomes. Evidence for associations with physical disorder and the disease burden of tobacco use, alcohol consumption, and dietary factors underscores the public health importance of this work and the need for future studies. Intervening on indicators of built environment physical disorder – vacant lot remediation or neighborhood revitalization efforts – might be one strategy for reducing the burden of several health behavior risks of population health.

CRediT authorship contribution statement

Jesse J. Plascak: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Tatyana Desire-Brisard:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Darren Mays:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Brittney Keller-Hamilton:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Andrew G. Rundle:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Writing – original draft, Writing – review & editing. **Emma Rose:** Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Electra D. Paskett:** Funding acquisition, Resources, Supervision, Writing – original draft, Writing – review & editing. **Stephen J. Mooney:** Conceptualization, Investigation, Methodology, Project administration, Resources, Software, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This study was supported by funds from the Cancer Institute of New Jersey and National Cancer Institute (P30CA072720-19: Cancer Prevention and Control Pilot award to JJP, K07CA222158-01 to JJP). This study was also partly supported by the Columbia Population Research Center (P2CHD058486 to AGR), the Eunice Kennedy Shriver National Institute of Child Health & Human Development of the National Institutes of Health (1R01HD087460-01 to AGR), and the National Library of Medicine (R00LM012868 to SJM).

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pmedr.2023.102131.

References

Agorastos, A., Chrousos, G.P., 2022. The neuroendocrinology of stress: the stress-related continuum of chronic disease development. Mol. Psychiatry 27, 502–513.
Bader, M.D.M., Mooney, S.J., Lee, Y.J., Sheehan, D., Neckerman, K.M., Rundle, A.G., Teitler, J.O., 2015. Development and deployment of the Computer Assisted Neighborhood Visual Assessment System (CANVAS) to measure health-related neighborhood conditions. Health Place 31, 163–172.
Branas, C.C., South, E., Kondo, M.C., Hohl, B.C., Bourgois, P., Wiebe, D.J., MacDonald, J. M., 2018. Citywide cluster randomized trial to restore blighted vacant land and its effects on violence, crime, and fear. Proc. Natl. Acad. Sci. USA 115, 2946–2951.
Brazil, N., 2022. The multidimensional clustering of health and its ecological risk factors. Soc. Sci. Med. 295.
Brown, Q.L., Milam, A.J., Smart, M.J., Johnson, R.M., Linton, S.L., Furr-Holden, C.D.M., Ialongo, N.S., 2014. Objective and perceived neighborhood characteristics and tobacco use among young adults. Drug and Alcohol Dependence 134, 370–375.
Bureau, U.S.C., Department of Commerce, E., Statistics, A., 2020. County Business Patterns, 2011-2016, https://www.census.gov/programs-surveys/cbp.html.
Burt, C.J., Kondo, M.C., Hohl, B.C., Gong, C.H., Bushman, G., Wixom, C., South, E.C., Cunningham, R.M., Carter, P.M., et al., 2022. Community greening, fear of crime, and mental health outcomes. Am. J. Community Psychol. 69, 46–58.
Butler, D.C., Petterson, S., Phillips, R.L., Bazemore, A.W., 2013. Measures of social deprivation that predict health care access and need within a rational area of primary care service delivery. Health Serv. Res. 48, 539–559.
Centers for Disease, C., Prevention, 2012. Methodologic changes in the Behavioral Risk Factor Surveillance System in 2011 and potential effects on prevalence estimates. MMWR. Morbidity and mortality weekly report 61:410-13.
Chauhan, P., Ahern, J., Galea, S., Keyes, K.M., 2016. Neighborhood context and binge drinking by race and ethnicity in New York City. Alcohol. Clin. Exp. Res. 40, 785–793.
Collaborators, G.B.D.C.R.F., 2022. The global burden of cancer attributable to risk factors, 2010–19: a systematic analysis for the Global Burden of Disease Study 2019. Lancet 400, 563–591.
Cooksey-Stowers, K., Schwartz, M.B., Brownell, K.D., 2017. Food swamps predict obesity rates better than food deserts in the united states. Int. J. Environ. Res. Public Health 14.
Ford, E.S., Zhao, G.X., Tsai, J., Li, C.Y., 2011. Low-risk lifestyle behaviors and all-cause mortality: findings from the national health and nutrition examination survey III mortality study. Am. J. Public Health 101, 1922–1929.
Furr-Holden, C.D.M., Lee, M.H., Milam, A.J., Johnson, R.M., Lee, K.S., Ialongo, N.S., 2011. The growth of neighborhood disorder and marijuana use among urban adolescents: a case for policy and environmental interventions. J. Stud. Alcohol Drugs 72, 371–379.
Isgor, Z., Powell, L., Rimkus, L., Chaloupka, F., 2016. Associations between retail food store exterior advertisements and community demographic and socioeconomic composition. Health Place 39, 43–50.
Islami, F., Goding Sauer, A., Miller, K.D., Siegel, R.L., Fedewa, S.A., Jacobs, E.J., McCullough, M.L., Patel, A.V., Ma, J., et al., 2018. Proportion and number of cancer cases and deaths attributable to potentially modifiable risk factors in the United States. CA Cancer J. Clin. 68, 31–54.

Keyes, K.M., McLaughlin, K.A., Koenen, K.C., Goldmann, E., Uddin, M., Galea, S., 2012. Child maltreatment increases sensitivity to adverse social contexts: neighborhood physical disorder and incident binge drinking in Detroit. Drug Alcohol Depend. 122, 77–85.

Maani, N., Collin, J., Friel, S., Gilmore, A.B., McCambridge, J., Robertson, L., Petticrew, M.P., 2020. Bringing the commercial determinants of health out of the shadows: a review of how the commercial determinants are represented in conceptual frameworks. Eur. J. Public Health 30, 660–664.

Mayne, S.L., Jose, A., Mo, A., Vo, L., Rachapalli, S., Ali, H., Davis, J., Kershaw, K.N., 2018. Neighborhood disorder and obesity-related outcomes among women in Chicago. Int. J. Environ. Res. Public Health 15.

McEwen, B.S., 1998. Protective and damaging effects of stress mediators. New Engl. J. Med. 338, 171–179.

Messer, L.C., Vinikoor-Imler, L.C., Laraia, B.A., 2012. Conceptualizing neighborhood space: consistency and variation of associations for neighborhood factors and pregnancy health across multiple neighborhood units. Health Place 18, 805–813.

Meyers, J.L., Cerda, M., Galea, S., Keyes, K.M., Aiello, A.E., Uddin, M., Wildman, D.E., Koenen, K.C., 2013. Interaction between polygenic risk for cigarette use and environmental exposures in the Detroit neighborhood health study. Transl. Psychiat. 3.

Mooney, S.J., Bader, M.D., Lovasi, G.S., Neckerman, K.M., Rundle, A.G., Teitler, J.O., 2018. Using universal kriging to improve neighborhood physical disorder measurement. Sociol. Methods Res. 0049124118769103.

Mudryj, A.N., Riediger, N.D., Bombak, A.E., 2019. The relationships between health-related behaviours in the Canadian adult population. BMC Public Health 19.

O'Brien, D.T., Farrell, C., Welsh, B.C., 2019. Broken (windows) theory: A meta-analysis of the evidence for the pathways from neighborhood disorder to resident health outcomes and behaviors. Soc. Sci. Med. 228, 272–292.

O'Brien, D.T., Ristea, A., Hangen, F., Tucker, R., 2022. Different places, different problems: profiles of crime and disorder at residential parcels. Crime Sci. 11.

Park, C.L., Iacocca, M.O., 2014. A stress and coping perspective on health behaviors: theoretical and methodological considerations. Anxiety Stress Coping 27, 123–137.

Plascak, J.J., Llanos, A.A.M., Qin, B., Chavali, L., Lin, Y., Pawlish, K.S., Goldman, N., Hong, C.C., Demissie, K., et al., 2020a. Visual cues of the built environment and perceived stress among a cohort of black breast cancer survivors. Health Place 67, 102498.

Plascak, J.J., Rundle, A.G., Babel, R.A., Llanos, A.A.M., LaBelle, C.M., Stroup, A.M., Mooney, S.J., 2020b. Drop-and-spin virtual neighborhood auditing: assessing built environment for linkage to health studies. Am. J. Prev. Med. 58, 152–160.

Plascak, J.J., Schootman, M., Rundle, A.G., Xing, C., Llanos, A.A.M., Stroup, A.M., Mooney, S.J., 2020c. Spatial predictive properties of built environment characteristics assessed by drop-and-spin virtual neighborhood auditing. Int. J. Health Geogr. 19, 21.

Plascak, J.J., Rundle, A.G., Xu, X.Y., Mooney, S.J., Schootman, M., Lu, B., Roy, J., Stroup, A.M., Llanos, A.A.M., 2022. Associations between neighborhood disinvestment and breast cancer outcomes within a populous state registry. Cancer 128, 131–138.

Raleigh, E., Galster, G., 2015. Neighborhood disinvestment, abandonment, and crime dynamics. J. Urban Aff. 37, 367–396.

Randall, M., Stern, A., Su, Y., 2021. Five Ethical Risks to Consider before Filling Missing Race and Ethnicity Data.

Rubin, D.B., 2004. Multiple Imputation for Nonresponse in Surveys. John Wiley & Sons.

Sampson, R.J., Raudenbush, S.W., 2004. Seeing disorder: neighborhood stigma and the social construction of "broken windows". Soc. Psychol. Q. 67, 319–342.

Wiss, D.A., Avena, N., Gold, M., 2020. Food addiction and psychosocial adversity: biological embedding, contextual factors, and public health implications. Nutrients 12.