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Role of Walkability, Bike Infrastructure, and Greenspace in Combatting Chronic Diseases: A Heterogeneous Ecological Analysis in the United States

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ABSTRACT

Associations of built and natural environment and bike infrastructure features with neighborhood-level hypertension and obesity prevalence across the U.S. are not well explored. Identifying the environmental determinants of neighborhood-level disease prevalence can support community-based nonpharmacologic interventions. Additionally, little is known about the extent of heterogeneity in built and natural environment impacts. Quantifying heterogeneity can help identify places where the greatest health gains can be obtained from infrastructural investments. Using a new neighborhood-level database, we assessed heterogeneous associations of neighborhood built and natural environment and bike infrastructure features with nationwide hypertension and obesity rates using a simultaneous quantile regression framework. A walkability index, access to green space, and bicycle infrastructure were negatively correlated with hypertension and obesity after controlling for social vulnerability. The associations of key environmental and bike infrastructure factors exhibited considerable heterogeneity. For a unit increase in the walkability index, the potential reduction in hypertension prevalence at the 10^{th} percentile was 3.4 times the reduction at the 95^{th} percentile. Likewise, the potential reduction in obesity prevalence at the 10^{th} percentile was 1.8 times the reduction at the 95^{th} percentile. Provision of on-street and off-street bike lanes was correlated with lower hypertension and obesity, although the impacts varied across the quantiles of health outcomes. Urban design policies promoting walkability, providing on-street and off-street bicycle facilities, and enhancing greenspace can be important strategies to combat hypertension and obesity. Our study underscores the importance of incorporating environmental features into future iterations of national disease prevalence data programs in the U.S.
Keywords: Chronic Disease; Hypertension & Obesity; Built and Natural Environment; Bike Infrastructure; Quantile regression.

1. INTRODUCTION

Designing socially resilient and healthy transportation systems is a key to sustainable cities and societies (Megahed and Ghoneim 2020, Nieuwenhuijsen 2020, Reisi et al. 2020). The design of urban transport networks shapes individual activity patterns (Badland and Schofield 2005, Sallis et al. 2016) that impact health, including chronic and infectious disease outcomes (Sallis et al. 2012, Frank et al. 2019, Wali 2023). Among chronic diseases, hypertension and obesity are major public health issues worldwide. Hypertension affects an estimated 1.28 billion adults aged 30-79 years worldwide (WHO 2021). In the U.S., hypertension was diagnosed as a contributing cause in over half a million deaths – costing the nation $131 billion in annual health costs (CDC 2019). The most recent U.S. Surgeon General’s Call-to-Action identified hypertension control as a national priority (HHS 2020). The increasing prevalence of obesity worldwide – an epidemic defined as “globesity” by the World Health Organization (WHO 2020) – is also a major public health issue. The number of obese adults worldwide has more than doubled since 1990, with an estimated 890 million people living with obesity in 2022 (WHO 2024). Further, hypertension and obesity often precede the onset of other diseases and are major modifiable risk factors for non-communicable diseases including cardiovascular diseases (Anand and Yusuf 2011, Powell-Wiley et al. 2021), stroke (Kernan and Dearborn 2015, Wajngarten and Silva 2019), cancer (Wolin et al. 2010, Mouhayar and Salahudeen 2011), dementia (Nagai et al. 2010, Anjum et al. 2018), and Alzheimer's disease (Nagai et al. 2010, Kiliaan et al. 2014). Evidence also suggests that chronic diseases including obesity and hypertension are key predictors of mortality from infectious diseases, including COVID-19 (Frank and Wali 2021, Mollalo et al. 2021). Collectively referred to as the "vicious twins" in the diseases of civilization (Leggio et al. 2017), preventive measures to control hypertension and obesity are a key public health priority (James 2017) and a key to achieving the sustainable development goal of reducing premature mortality from cardiovascular diseases (Global SDG Indicator Platform 2019).

Built and natural environment features of cities, where people live, work, and play, are key focal points (Dadvand et al. 2014, McCunn 2021) and can be designed or retrofitted to reduce hypertension and obesity (Cerin et al. 2013). The relationship between the environment and chronic disease is primarily influenced by health behaviors (Frank et al. 2019, Su et al. 2019), such as increased physical activity and active travel, in more walkable and greener environments with dense infrastructure, connected street networks, and diverse land uses (Wali et al. 2022b). Current evidence, mostly from individual-level studies, suggest lower prevalence of hypertension and obesity in more walkable (Li et al. 2009, Feng et al. 2010, Sallis et al. 2012, Sarkar et al. 2018, Chandrabose et al. 2019, Adhikari et al. 2021, Prados et al. 2023) and greener neighborhoods (Dadvand et al. 2014, Bauwelinck et al. 2020, Zhao et al. 2022, Bu et al. 2023, Cerin et al. 2023, Liu et al. 2023b, Mayne et al. 2023, Sharifi et al. 2024, Zeng et al. 2024). In particular, walkability and greenspace benefits in relation to chronic disease mitigation are established in regional (Prados et al. 2023) as well as population-based health surveillance datasets (Adhikari et al. 2021). Besides macro-level walkability characteristics (e.g., density, design, and diversity) (Cervero and Kockelman 1997), the literature also points to the need for pedestrian-bicyclist infrastructure to maximize the health benefits walkability can produce by enhancing safer accessibility to diverse land uses and activity types (Litman 2015, Pan et al. 2021, Wali and Frank 2024).

1.1. Research Gaps

Compared to individual-level studies, the evaluation of population-level chronic disease prevalence at a finer geographic scale (e.g., census tract) has received less attention. Neighborhood-level disease prevalence is a key indicator for disease surveillance purposes (Klompas et al. 2017, Aerts et al. 2020, Kwan and Saragih 2020). Identifying its determinants across U.S. communities can further enable community-based nonpharmacologic interventions (Economos and Irish-Hauser 2007, Heath et al. 2012, Mensah et al. 2018, HHS 2020, Kong and Zhang 2020), including in areas where direct survey estimates are not valid due to multiple factors including low response rates, lack of resources, or limited sample sizes (Ghosh and Rao 1994, Zhang et al. 2014).

A handful of studies have examined the links between contextual variables and neighborhood-level chronic disease prevalence across the U.S. (Fitzpatrick et al. 2018, Liu et al. 2018a, Liu et al. 2018b, Quick et al. 2020). These studies have provided useful insights into the impacts of unhealthy behaviors (e.g., binge drinking), preventive measures (e.g., health insurance), and sociodemographic factors on chronic disease prevalence. However, key gaps remain.

First, no study to our knowledge has assessed built and natural environment features in relation to neighborhood-level hypertension and obesity prevalence across the nation. Thus far, most studies are individual-based and regionally focused as noted above. Besides macro-level walkability and greenspace, the associations of biking infrastructure with neighborhood chronic disease prevalence are not well explored. In the U.S., assessments of neighborhood-level chronic disease prevalence have mostly harnessed the US CDC's PLACES (or its predecessor 500 Cities Project) database (Fitzpatrick et al. 2018, Liu et al. 2018a, Liu et al. 2018b, Quick et al. 2020). The PLACES database provides nationally comparable neighborhood disease prevalence estimates derived largely from demographic and socioeconomic factors using individual-level health survey data (discussed later in detail). Given the now well-documented impacts of the built and natural environment on chronic diseases (Sallis et al. 2012), it is important to assess how built and natural environment characteristics correlate with independently derived estimates of chronic disease prevalence which are intended for national use. Any correlation, if exists, would highlight the need to explore the inclusion of built and natural environment features in developing future versions of national disease prevalence data programs (e.g., PLACES project) in the U.S.

Second, previous studies have not examined unobserved heterogeneity in the impacts of built and natural environment and bike infrastructure features within the context of neighborhood-level chronic disease burden. This is important since behavioral pathway is among the key mechanisms documenting the impacts of place on individual behaviors and health (Wilkie et al. 2018, Frank et al. 2019) and the interactions between individuals and their surrounding environments are often characterized by considerable heterogeneity (Chesson and Rosenzweig 1991, Montiglio et al. 2013, Chen and Li 2021, Wali et al. 2022a). Besides, chronic diseases have a multitude of underlying causes, and data on many of these factors are often missing in even the most comprehensive health databases. The omission of such factors leads to variations in the impacts of observed exogenous factors. Unobserved heterogeneity in this context is defined as potential variations in the associations of key environmental factors due to systematic variations in unobserved factors (e.g., attitudes, perceptions, or accessibility to medical facilities, to name a few) (Wali et al. 2022a). Such heterogeneity is not only limited to ecological analyses, as individual-level studies have also shown considerable heterogeneity in the magnitude and direction of environmental impacts on health outcomes (Wali et al. 2022a). In this context, unobserved heterogeneity impacts originate at the individual level and can be manifested at the ecological level. With the implications of omitting such health-relevant unobserved factors now increasingly becoming known (Zarulli 2016, Wali 2023), it is important to harness methods that can capture potential heterogeneous associations. The quantification of heterogeneous associations can provide policy-relevant insights into places where the greatest health gains from investments in the built and natural environment and bike infrastructure can be made.

1.2. Research Objective

Given these gaps, the present study evaluates how objective built and natural environment features and bike infrastructure facilities correlate with neighborhood-level hypertension and obesity prevalence across the U.S, adjusting for spatial variations across the U.S. urban-rural continuum (metropolitan, micropolitan, small towns, and rural areas) and U.S. census regions. We adjust for social vulnerability as an important confounder of the relationships between environmental factors and disease prevalence (Turrell et al. 2013, Roberts et al. 2015, Wali 2023). Methodologically, we assess heterogeneity in the protective role of built and natural environment measures and bike facilities by assessing the magnitude of environmental impacts across the distributions of hypertension and obesity rates. These objectives are achieved by integrating a national disease surveillance database by the U.S. Centers for Disease Control and Prevention (CDC) with high-resolution objectively assessed built and natural environmental, pedestrian/bicyclist infrastructure, and social vulnerability measures. The resulting new information is critical to the development of place-based interventions for hypertension and obesity control with implications for infrastructure monitoring, investment prioritization, and funding[1].

2. METHODS

2.1. Design & Sample

We harnessed an ecological study design with neighborhood-level (census tract) data on health outcomes, social deprivation, and built/natural environment features for the entire U.S. A new neighborhood-level health dataset is created by pooling information from three unique datasets: (1) PLACES: Local Data for Better Health by the Centers for Disease Control and Prevention (CDC) and Robert Wood Johnson Foundation (RWJF) (CDC 2020b), (2) the National Environmental Database (NED) by the RWJF, and (3) the CDC's Social Vulnerability Database. The census-tract served as a unit of analysis and is the smallest level of geography for which chronic disease outcome data are consistently available.

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[1] We searched Web of Science, PubMed, Transportation Research International Documentation, and Google Scholar for articles published from inception till Feb 28, 2023, analyzing neighborhood-level hypertension and obesity prevalence in the United States in relation to built and natural environment features, and provision of bicycle facilities, using the key terms: ("obesity prevalence" OR "hypertension prevalence" OR "high blood pressure prevalence") AND ("built environment", "natural environment", "walkability", "green space") AND ("heterogeneity"). Although we found few studies examining the relationships between neighborhood features and chronic disease (mainly, obesity) prevalence in the US (as discussed above), we did not find any studies examining neighborhood-level hypertension and obesity prevalence and its links with built and natural environment features. Moreover, we did not find studies examining heterogeneity in the impacts of neighborhood built/natural environment features on hypertension and obesity.

2.1.1. Outcomes: Neighborhood Chronic Disease Prevalence

Data on hypertension and obesity prevalence were drawn from the recent PLACES database (2020 data release). As an expansion of the original 500 Cities Project, the **P**opulation **L**evel **A**nalysis and **C**ommunity **Es**timates (PLACES) database provides much-needed census-tract level, nationally comparable, small-area estimates for health outcomes in the U.S. (CDC 2020b). In addition to the expanded geographic coverage beyond the 500 most populous cities, PLACES expands upon the 500 Cities Project by incorporating innovations in producing valid small-area health estimates for both urban and rural areas, see (CDC 2020b) for details. These data are intended to advance health by informing the development and application of targeted public health interventions. The census tract-level PLACES estimates are based on individual-level health survey data from the CDC's Behavioral Risk Factor Surveillance System survey[2] (Zhang et al. 2014). Table A1 shows the geographic resolution, time frame, and data sources of all study variables.

2.1.2. Exposures: Built and Natural Environment Features

Built environment data at the census tract level were derived from the most recent version of the NED nationwide repository of key environmental features covering the entire U.S. (Wali et al. 2021). Built environment measures used in this study relate to (1) density, (2) street connectivity, (3) diversity, (4) access to transit, and (5) automobile use. Residential density (housing units/acre of developable land) represented built environment compactness (Cervero and Kockelman 1997). Diversity in jobs was captured through an eight-tier employment entropy (mix) characterizing access to different employment types: retail, office, industrial, service sector, entertainment, education, healthcare, and public administration (Cervero and Kockelman 1997). A weighted street intersection density (eliminating auto-oriented intersections) (count/square km.) measure was used as a proxy for pedestrian-oriented network connectivity (Frank et al. 2005). Access to transit was captured by the count of transit stops (all rail and bus modes) within a neighborhood. Finally, the annual average household vehicle miles traveled (VMT) was used as a measure of car dependence (Brownstone 2008) – picking up the effect of neighborhood-level environmental features supporting car dependence and hindering active travel. A composite national walkability index (NWI) was created combining the above measures to circumvent the multicollinearity issue arising from the use of individual built environment features (Wali et al. 2021). The data were standardized when calculating the NWI. A normalization process was used to make the underlying NWI variables with different units comparable and easily combine them on the same scale. Normalization determines the number of standard deviations each value is from the mean of that

[2] Standardized definitions of hypertension and obesity are adopted in PLACES (CDC 2020b). The two primary outcomes were defined as: (1) High Blood Pressure: "Respondents aged ≥18 years who report ever having been told by a doctor, nurse, or other health professional that they have high blood pressure. Women who were told high blood pressure only during pregnancy and those who were told they had borderline hypertension were not included.", and (2) Obesity: "Respondents aged ≥18 years who have a body mass index (BMI) ≥30.0 kg/m² calculated from self-reported weight and height." (CDC 2020b).

set of variable values. Each of the five component variables (shown in Table 1) was normalized using z-score values and then combined to calculate the NWI using the formulation shown in Table 1. Formulation and application of the NWI have been published elsewhere (Wali et al. 2021).

To capture bicyclist-oriented infrastructure design elements, facility densities (per mi.) of off-street (separated multi-use pathways) and on-street (bike lanes) within 100 ft. crow-fly distance around tract boundaries were calculated. A bicycle facility density measure was calculated to quantify the ratio of total linear miles of bicycle facilities compared to total linear miles of walkable (road segments where pedestrians are permitted to traverse with limited access roads and entry ramps removed) roadways. Multiple data sources were used to compute these measures, as shown in Table A1. For the state of California, a bicycle facility data inventory was developed from data furnished by Caltrans (California Department of Transportation, 15 California Metropolitan Planning Organizations (MPOs), and 8 California Regional Transportation Planning Organizations (RTPOs) that had bicycle infrastructure data available). For the rest of the U.S., data was acquired from Open Street Map (OSM) sources for both types of bicycle facilities. Any gaps in bicycle facility coverage in California were filled by OSM data where available, while prioritizing state and regional government sources and excluding overlapping features to prevent duplication. Five-year (2015-2019) pedestrian and bicyclist-involved fatal traffic crash density per 100,000 residential population were also used, using source data from the National Highway Traffic Safety Administration (Table A1).

Finally, natural environment variables were harnessed including tree canopy and access to developed parks represented by the number of parks of any type or size[3]. Tree canopy cover is defined as the percentage of land covered by the horizontal projection of tree crowns. The base data sources used for natural environment measures are shown in Table A1. To account for variations across spatial sub-groups, a four-tier urban-rural continuum code (metropolitan, micropolitan, small towns, and rural areas) was used to capture variations in urbanity and rurality across the country (Morrill et al. 1999, USDA 2010). The rural-urban community area (RUCA) codes by the USDA's Economic Research Service classify U.S. census tracts using measures of urbanization, population density, and daily commuting patterns (Morrill et al. 1999). These codes are exogenous to the NWI as the variables used by USDA in the RUCA codes do not constitute NWI. Moreover, all the census tracts were classified into nine U.S. regions based on the Census Bureau Regions and Divisions classification system (US Census 2021). Table 1 shows the definitions and formula for each of the built environment metrics and walkability index.

[3] Park data were acquired from the U.S. Geological Survey (USGS) Protected Areas Database (PAD) and OSM Park Inventory Source (Table A1). Only parks with developed infrastructure were included with natural or conservation areas excluded from the inventory. Comprehensive and consistent attribute information on the date of park construction was not available in either database. Both datasets likely have very few parks that were developed after 2018 (collection time of health data), especially the USGS PAD. However, it was impossible to exclude newer parks since there are no construction attributes available for either database.

2.1.3. Social Deprivation and Vulnerability

Neighborhood social deprivation and vulnerability can be an important confounder of the association between the built/natural environment (key exposure) and disease prevalence (Turrell et al. 2013, Roberts et al. 2015, Liao et al. 2023, Wali 2023). To adjust for social deprivation, we harnessed Social Vulnerability Index (SVI) data from the US CDC's Agency for Toxic Substances and Disease Registry (ATSDR) (Flanagan et al. 2011, CDC 2020a). The purpose of the SVI is to assist decision-makers in identifying communities with a high risk of a disease outbreak (CDC 2020a). The SVI ranked every census tract on 15 social factors grouped into four related themes: 1) socioeconomic status, 2) household composition and disability, 3) minority status and language, and 4) housing type and transportation (see Table 2). Based on percentiles, each tract is ranked among all census tracts in the U.S. for each of the individual census variables, four themes, and an overall vulnerability theme (a composite measure of the four themes combined) (Table 2). Theme-specific rankings are derived by summing the percentiles for each Census variable comprising each of the four themes and ordering the summed percentiles across all census tracts. The percentile rankings for the four themes are summed and the census tracts are re-ordered to calculate an overall percentile ranking (CDC 2020a). The overall SVI ranges between 0 and 1 with higher values indicating greater social vulnerability or more unfavorable conditions related to the specific themes (Table 2) (Flanagan et al. 2011, CDC 2020a). We multiplied the SVI by 100 for scaling purposes in the forthcoming models.

The final data matrix contains data on 71,913 census tracts for all incorporated variables. Environmental data from the NED and chronic disease estimates from PLACES were available for 74,133 and 72,048 census tracts nationwide, respectively. Data on neighborhood-level deprivation from the CDC were available for 73,469 census tracts. A total of 72,048 census tracts were represented in the three data sources (NED, PLACES, and CDC's social vulnerability database). Of these census tracts, 71,913 census tracts (99.8%) had complete data on the built environment, social deprivation, and chronic disease measures considered in this study.

TABLE 1. Description and Formulation of Built Environment Variables

Variable name	Description	Formulation
Residential density	Gross residential density on unprotected land (D1A).	This measure is calculated as number of housing units per acre of unprotected land. Gross residential density = number of housing units (both single family and multi-family) / area of developable land in acres (water bodies and conservation areas excluded)
Street network intersection density	Street intersection density (weighted, auto-oriented intersections eliminated) (D3B).	This measure is calculated by developing a weighted sum of component intersection density metrics including three-leg and ≥ 4 legs multi-modal intersections (D3BMM3 and D3BMM4) and three-leg and ≥ 4 legs pedestrian-oriented (D3BPO3 and D3BPO4) intersections. To reflect support for pedestrian and bicyclist mobility, auto-oriented intersections were assigned zero weight. Three-way intersections were assigned relatively lower weights compared to four-way intersections since the latter promotes street connectivity more effectively. $\mathrm{D3B} = \dfrac{(0.667 * \mathrm{D3BMM3}) + (0.667 * \mathrm{D3BPO3}) + \mathrm{D3BMM4} + \mathrm{D3BPO4}}{total\ land\ area\ in\ acres}$ Eq. (1)
Employment mix	Eight-tier employment entropy (D2B_E8MIXA).	This measure is based on the 8-tier employment categories to calculate employment mix (entropy). All eight employment types are used in the employment entropy denominator. It is calculated as: $\mathrm{D2B\_E8MIXA} = -\dfrac{\mathrm{E}}{\ln(8)}$ Eq. (2) Where: E represents a composite index combining eight different employment types as a ratio of total employment in a block group. Eight employment types include retail, office, industrial, service sector, entertainment, education, healthcare, and public administration. For formulation of E, see (Wali et al. 2021).
Access to transit	Number of transit stops in a block group (DAT).	This measure captures the number of transit stops within a census block group. Those block groups with no transit stop but located in urbanized areas with access to the nearest transit stop within 0.64 miles (or 15-minute walk) were assigned a value of one stop to distinguish them from block groups with no transit access.
Vehicle Miles Travelled	Annual household vehicle miles traveled (VMT).	Modeled VMT for regional median family income by the US Department of Transportation.
Walkability Index	National walkability index	This variable is calculated as a composite measure of the above built environment features related to connectivity, diversity, density, transit, and automobile use. Using normalized z-score value of each of the variables, the formulation is: $Walkability\ Index = (D1A) + (D3B) + \mathrm{D2B\_E8MIXA} + DAT + [(-1) * VMT]$ Eq. (3)

TABLE 2. Underlying Themes and Variables of the Social Vulnerability Index.

Overall Vulnerability	<u>**Theme 1:**</u> **Socioeconomic Status**	Below poverty	Percent individuals below poverty
		Unemployed	Percent civilians (age 16+) unemployed
		Income	Per capita income (mean income in census tract)
		No high school diploma	Percent individuals (age 25+) with no high school diploma
	<u>**Theme 2:**</u> **Household Composition & Disability**	Aged 65 or older	Percent individuals 65 years of age or older
		Aged 17 or younger	Percent individuals 17 years of age or younger
		Civilian with a disability	Percent of civil individuals of age 5 years or older with a disability
		Single-parent households	Percent of single-parent households with children under 18 years old.
	<u>**Theme 3:**</u> **Minority Status & Language**	Minority	Percent minority (all individuals except white, non-Hispanic)
		Aged 5 or Older who speaks English "less than well"	Percent individuals 5 years or older who speak English less than "well"
	<u>**Theme 4:**</u> **Housing Type & Transportation**	Multi-unit structures	Percent housing units with 10 or more units in a structure
		Mobile homes	Percent housing units that are mobile homes
		Crowding	Percent total occupied housing units with >1 person per room
		No vehicle	Percent households with no vehicle available
		Group quarters	Percent individuals who are in group quarters, both institutionalized (e.g., correctional institutions, nursing homes) and non-institutionalized (e.g., college dormitories, military quarters).

2.2. Descriptive & Modeling Methods

Descriptive analysis was initially performed to understand data distributions and assess measures of central tendency (mean and medians) and dispersion (standard deviations and interquartile ranges). Visualizations to assess distributional variations of response outcomes were developed. Spearman's rank correlations were visualized to understand bivariate dependencies (Zar 2005).

Given the continuous nature of the response outcomes, a traditional fixed parameter regression framework can be used to model the determinants of neighborhood disease prevalence. However, the linear regression framework is restrictive as it only models the conditional mean of the response outcomes as a function of exogenous factors. A conditional mean approximation can provide inaccurate insights when the data are characterized by unobserved heterogeneity. Robust to heteroskedasticity and non-normal distribution of error terms (Koenker 2010), a quantile regression framework allows an examination of how specific quantiles (instead of the conditional mean) of the response outcomes vary as a function of exogenous factors (Wali et al. 2022c, Yang et al. 2024). As opposed to minimizing the mean squared errors in a standard regression framework, quantile regression minimizes a weighted sum assigning asymmetric penalties for over-prediction and under-prediction (Koenker 2010, Wali et al. 2022c). For a specific quantile q, the asymmetric penalties are $(1-q)|\aleph_i|$ and $q|\aleph_i|$ for over-and under-prediction, respectively (Koenker 2010). The quantile-specific error distribution is derived as (Koenker and Hallock 2001, Koenker 2010):

$$\aleph_i^q = Y_i - \hat{\beta}_0^q - \sum_{j=1}^{K} \hat{\beta}_j^q x_{ij} \tag{4}$$

Where: $\aleph_i^q$ is a vector containing model residuals for neighborhood i at quantile q; $\hat{\beta}_0^q$ is a vector of quantile-specific intercepts; $\hat{\beta}_j^q$ is a vector of quantile-specific estimable parameters associated with exogenous variable j (j = 1, 2, 3, …, K); and x_{ij} is the data matrix containing exogenous variables j across i neighborhoods. The estimable parameters can be estimated by minimizing the following objective function (Koenker and Hallock 2001, Koenker 2010):

$$\sum_{i:y_i \geq \hat{B}^q X_i}^{N} \left(q \left| y_i - \hat{\beta}_0^q - \sum_{j=1}^{K} \hat{\beta}_j^q x_{ij} \right|\right) + \sum_{i:y_i \leq \hat{B}^q X_i}^{N} \left((1-q)\left| y_i - \hat{\beta}_0^q - \sum_{j=1}^{K} \hat{\beta}_j^q x_{ij} \right|\right) \tag{5}$$

Where: $\hat{B}^q$ is a quantile-specific vector of all estimable parameters (including quantile-specific intercept terms). By minimizing the objective function in Eq. (5) through linear programming techniques, the final model function form is given as:

$$Y_i^q = \text{Prevalence rates}_{q(0.10,0.25,0.50,0.75,0.95)} = \hat{\beta}_0^q + \sum_{\mathrm{j}=1}^{K} \left(\hat{\beta}_j^q x_{ij}\right) + \aleph_i^q \tag{6}$$

Compared to independent quantile models (Koenker 2010), the quantile estimates were computed using simultaneous-quantile regressions to capture covariances among parameter estimates at different quantiles. Estimates of variance and covariances accounting for between-quantile blocks were obtained by 250 bootstrapped samples generally sufficient for unbiased estimates (DeLisi et al. 2011). Further, quantile regression models at continuous quantiles ranging from 0 to 1 (in increments of 0.1) were developed to understand the impacts of built and natural environment features across the entire spectrum of the distributions of response outcomes[4,5]. To examine sensitivity to exposures, the results from these estimations were used to create visualizations of covariate effects at continuous quantiles of the response outcomes.

[4] We note that quantile regression implies linearity and homoscedastic errors, but these assumptions are only conditional on specific quantiles of the response variable (Koenker 2017). This provides far greater flexibility compared to traditional fixed parameter models, as the assumptions of linearity and equal variance are far less restrictive when assessing specific fine-grained quantiles of the response variable (Koenker and Hallock 2001, Koenker 2017). In other words, the forthcoming results imply linear associations and homogenous errors only within, and not across, each of the fine-grained quantiles being modeled. Overall, the property of conditional quantile functions (as opposed to mean function) for Y|X makes quantile regression quite robust to outliers, long-tail distributions, and model misspecification (Koenker and Hallock 2001, Beyerlein 2014, John 2015, Huang et al. 2017), in addition to detecting heterogeneous impacts that are of interest in the present study (Wali et al. 2022c).

[5] The concept of heterogeneity more broadly entails variations in impact sizes due to different sources of variations, including unobserved, observed (systematic), and spatial heterogeneity. This study mainly focused on unobserved heterogeneity impacts. However, the framework used in this study indirectly captures systematic heterogeneity (non-linearities) and spatial dependencies by examining variations across the entire spectrum of chronic disease prevalence. Assessing systematic heterogeneity impacts is of interest in other contexts, e.g., to develop thresholds for environmental factors (Tu et al. 2021, Wali et al. 2021, Liu et al. 2023a). This is outside the scope of the present study but should be explored in future research. Furthermore, to accurately establish such environmental thresholds, it is important to simultaneously consider different types of heterogeneity which necessitates more advanced structural models (Bhat 2022, Ahn 2023, Kim and Mokhtarian 2023, Wali et al. 2023). This serves as a distinct methodological contribution for future research endeavors to pursue.

Environmental variables were treated as continuous whereas regional and urban/rural factors as categorical. Both linear and quantile regression analyses were performed for comparative purposes. Finally, multicollinearity was assessed in the final model specifications by computing Variance Inflation Factors (VIFs) and tolerance statistics (Washington et al. 2010). A VIF of greater than 10 and tolerance statistic of less than 0.1 for any exogenous factor indicate the presence of problematic multicollinearity requiring attention (Chatterjee and Price 1991). The final models did not have any problematic multicollinearity, as indicated by the VIFs and tolerance statistics of all the included exogenous factors being less than 4.2 and greater than 0.24, respectively.

3. RESULTS

3.1. Descriptive Statistics

With considerable heterogeneity, the average prevalence of hypertension and obesity is around 32% (Table 3). Figure 1 shows the asymmetry in the distributions of hypertension and obesity rates. The data are not rectangularly distributed, with strong skewness in the left (lower quantiles) and right (higher quantiles) tails of the distribution (Figures 1A through 1D). The 10^{th} and 95^{th} percentiles of hypertension prevalence equal 24% and 45·4%, respectively. Figure 2 reveals geographic disparities in the spatial distributions of hypertension and obesity prevalence nationwide. Hypertension prevalence is generally lower in the Northeastern, Western Pacific, and Western Mountain states and higher in the Southern states. Similar geographic patterns can be seen for obesity (Figure 2). This implies that the average hypertension and obesity rates cannot appropriately represent the distributional shapes.

TABLE 3. Descriptive Statistics of Key Variables.

Variable	Mean	SD	Median	IQR	Range
Chronic Disease Prevalence (%)					
High Blood Pressure / Hypertension	32.38	7.23	31.90	8.90	(5.4,67.2)
Obesity	32.15	6.86	32.10	9.20	(10.7,59.1)
Social Deprivation / Vulnerability (Social Vulnerability Index)					
SVI Theme 1: Socioeconomic status	50.01	28.86	50.02	49.96	(0,100)
SVI Theme 2: Household composition & disability	50.15	28.80	50.19	49.88	(0.04,100)
SVI Theme 3: Minority status & language	49.98	28.89	49.96	50.07	(0,100)
SVI Theme 4: Housing type & transportation	50.08	28.83	50.09	49.93	(0,100)
SVI overall theme	50.06	28.86	50.08	49.98	(0,100)
Built Environment					
Walkability Index (on scale 0 to 100)	22.69	7.04	21.61	9.35	(8.83,96.1)
Residential density (housing units / acre)	4.24	9.65	1.98	3.65	(0,300)
Street network intersection density (count / sq. km.)	73.88	60.25	65.34	94.02	(0,251.01)
Employment mix (on scale from 0 to 1)	0.55	0.15	0.56	0.20	(0,0.99)
Access to transit (stops)	2.84	4.84	0.67	4.00	(0,100)
Vehicle Miles Travelled	27961.13	5579.94	28736.51	7658.97	(20.75,39979)
Bike Infrastructure & Safety					
Buffered off-street length density per mi.	0.53	1.70	0	0.16	(0,44.96)
Buffered on-street (bike lane) length density per mi.	1.06	2.86	0	0.40	(0,58.04)
Buffered 5-Year pedestrian fatal crash density per 100k population	22.36	77.62	0	28.41	(0,8343.7)
Buffered 5-Year bicyclist fatal crash density per 100k population	25.65	85.41	0	32.84	(0,8343.7)
Natural Environment					
Buffered total park (any type) count	1.01	2.15	0.25	1.17	(0,55)
Unbuffered total park (any type) count	0.56	0.95	0.25	0.75	(0,44)
Buffered tree canopy coverage (%)	0.15	0.15	0.10	0.18	(0,0.98)
Urban-Rural Continuum (proportion)					
Metropolitan	0.82	0.38	1	0	(0,1)
Micropolitan	0.09	0.29	0	0	(0,1)
Small town	0.05	0.21	0	0	(0,1)
Rural	0.04	0.20	0	0	(0,1)
Regional Factors (proportion)					
North East: New England	0.05	0.21	0	0	(0,1)
North East: Mid Atlantic	0.14	0.35	0	0	(0,1)
Mid West: East North	0.16	0.37	0	0	(0,1)
Mid West: West North	0.07	0.26	0	0	(0,1)
South: South Atlantic	0.19	0.39	0	0	(0,1)
South: East South	0.06	0.24	0	0	(0,1)
South: West South	0.11	0.32	0	0	(0,1)
West: Mountain	0.07	0.26	0	0	(0,1)
West: Pacific	0.15	0.36	0	0	(0,1)

Notes: SD is standard deviation; IQR is interquartile range; SVI is social vulnerability index; N = 71,913 census tracts for all variables.

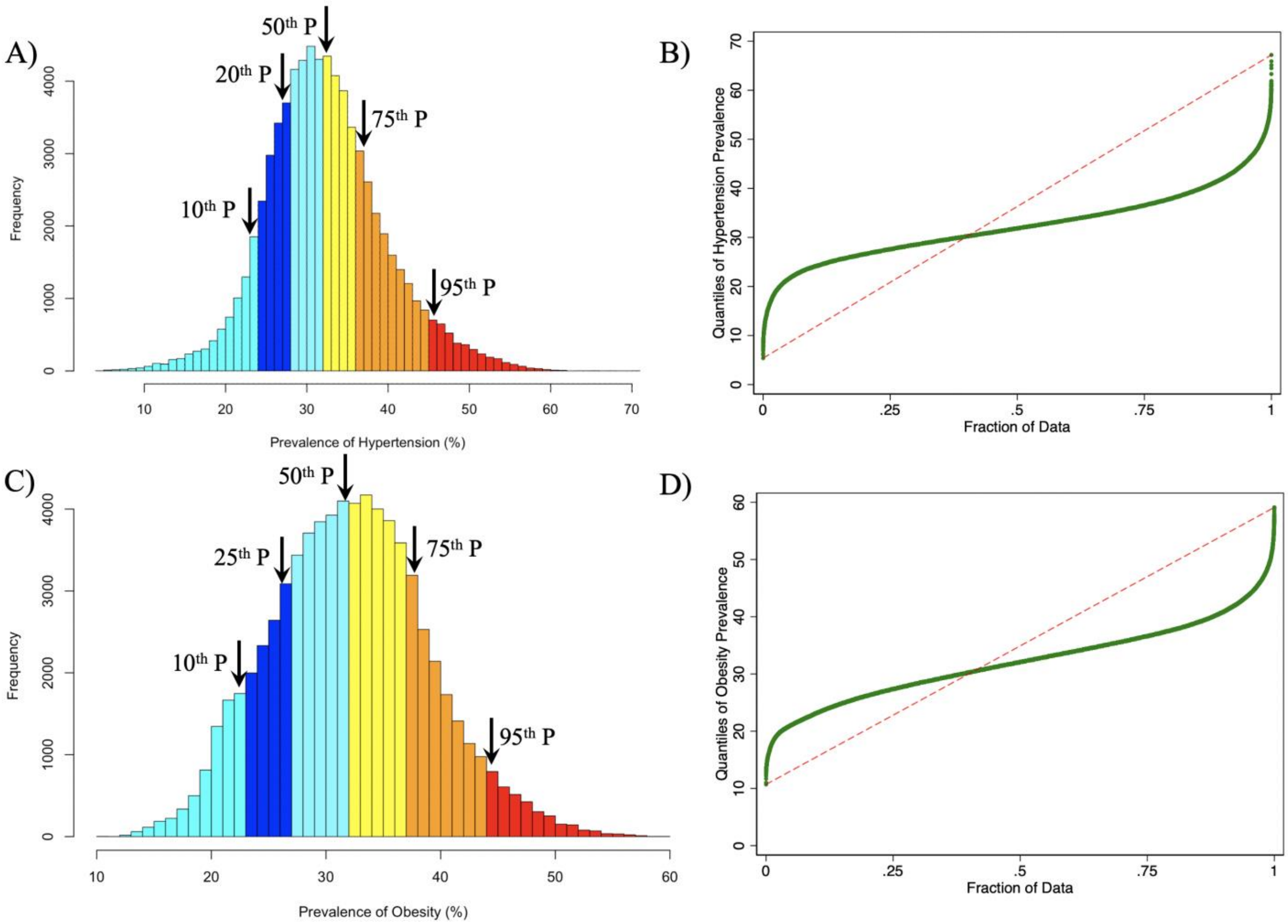

FIGURE 1. Distribution of Hypertension and Obesity Prevalence Rates.
Notes: A and C show the histograms for prevalence of hypertension and obesity, respectively (10^{th} P, 25^{th} P, 50^{th} P, 75^{th} P, and 95^{th} P indicate the respective percentiles). B and D show the empirical cumulative distribution functions of hypertension and obesity prevalence, respectively. Red dotted line represents the reference line. If the data were rectangularly distributed, all the points would lie on the red dotted line. Departures from the reference line indicate asymmetry and skewness.

Considerable variations in built and natural environment features are observed nationwide. A wide range of residential density, street network intersection density, employment mix, and access to transit are observed across the neighborhoods. In terms of walkability, the average walkability index is 22·69 with a range of 8·83 and 96·1 revealing significant nationwide variations. Similar patterns of large variations are found for bike infrastructure, traffic safety, and natural environment features (Table 3). The average social vulnerability index is 50.06 (on a scale 0 to 100; lower values indicate lower vulnerability) with an interquartile range of 49.98 revealing significant variations across neighborhoods. Figure 3 shows the unadjusted Spearman rank correlations of the chronic health outcomes with key environmental variables. Hypertension and obesity are negatively correlated with walkability index, access to parks, and bicycle infrastructure. Pedestrian-bicyclist fatal crash densities are positively correlated with hypertension and obesity prevalence. The two chronic diseases exhibit a moderate degree of correlation (Spearman rank correlation ≅ 0.7; Figure 3). Analysis of the correlations between obesity and hypertension prevalence levels revealed similarity and discrepancy patterns (see crosstab and non-parametric agreement measures in Table A2). While at least over half of the neighborhoods had concurrent levels (low-low, medium-medium, high-high) of obesity and hypertension prevalence, significant contrasts were also observed. Of all the neighborhoods with low obesity prevalence, around 57% had low hypertension prevalence, whereas the remaining neighborhoods exhibited medium and high levels of hypertension (Table A2). These discrepancy patterns support the separate analyses of the two key chronic diseases considered in this study.

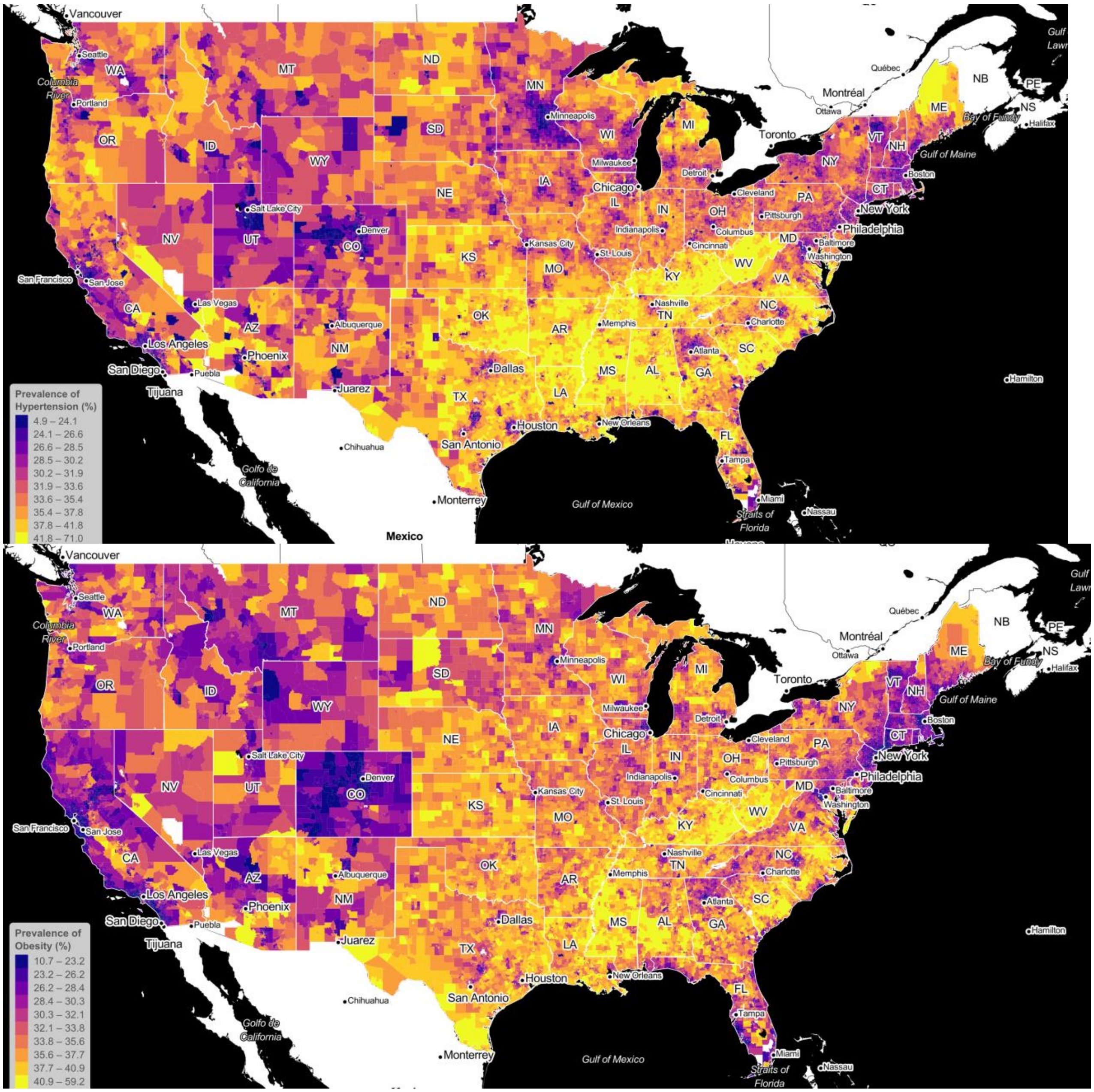

FIGURE 2. Nationwide Distribution of Hypertension and Obesity Prevalence Across Census-Tracts.

Notes: The breaks are defined according to quantiles of hypertension and obesity with probability values in [0,1] in an increment of 0.1. Alaska and Hawaii not shown.

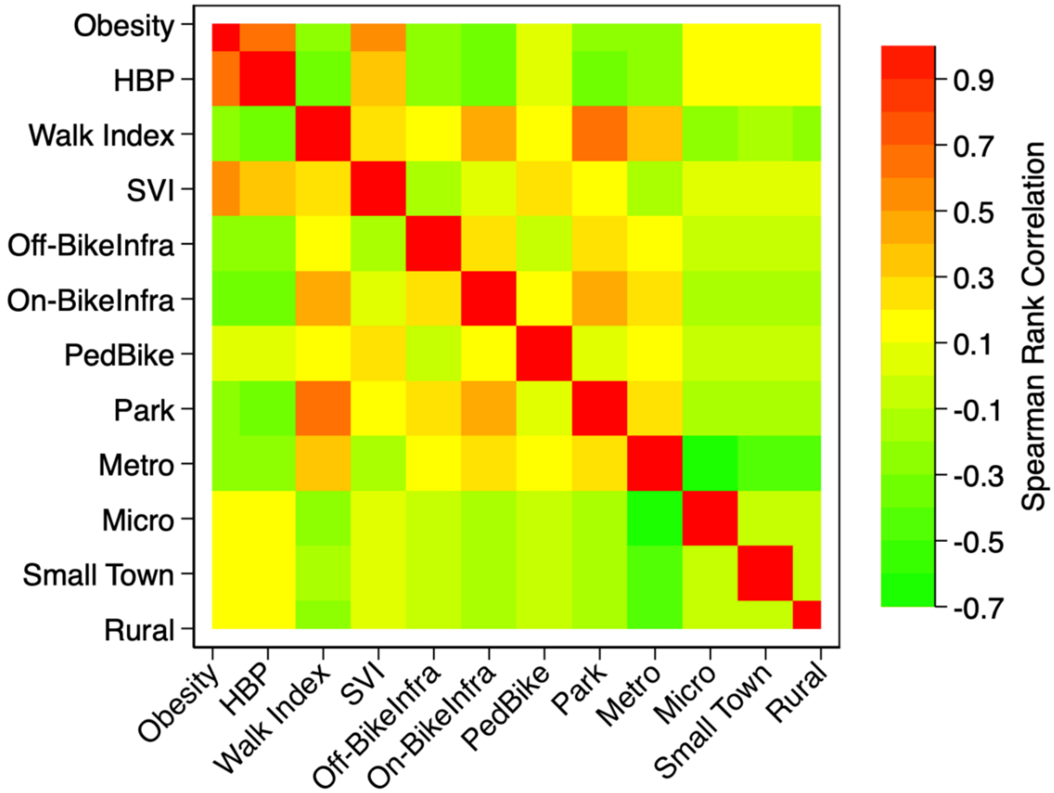

FIGURE 3. Spearman Rank Correlations of Environmental Features with Hypertension and Obesity Prevalence.

Notes: HBP: high blood pressure/hypertension; Walk Index: walkability index; SVI is social vulnerability index; Off_BikeInfra: buffered off-street length density per mi.; On_BikeInfra: buffered on-street (bike lane) length density per mi.; PedBike: 5-year pedestrian and bicyclist fatal crash density per 100,000 population; Park: buffered total park (any type) count; Metro & Micro: neighborhoods in metropolitan and micropolitan regions. Spearman's rank correlations of individual variables in the walkability index are not shown but are in the expected direction. P-values of Spearman's rank correlations are 0.0000 for all pairs of variables except PedBike and Off-BikeInfra (p-value of 0.1448).

3.2. Modeling Results

Tables 4 and 5 present the estimation results of fixed parameter and simultaneous quantile regression models for the prevalence of hypertension and obesity. Results from simultaneous quantile regression models at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentiles are provided for the two outcomes. All models account for social deprivation, regional and urban/rural indicators to account for potential variations and confounding. The β estimates in Tables 4 and 5 show the change in the mean (for fixed parameter regression) or quantile-specific conditional mean (for quantile regression) prevalence of hypertension and obesity with a unit increase in the continuous independent variable. For indicator variables, the β estimates show the resulting change in the outcomes for a switch from 0 (absence of a condition) to 1 (presence of a condition). Due to space considerations, Tables 4 and 5 show the results across selected quantiles that cover the entire range of the distribution. However, Figures 4 and 5 illustrate the β estimates of key exogenous factors at continuous quantiles of the response outcomes providing a more complete picture.

3.2.1. Neighborhood-level Correlates of Hypertension

Representing built environment, the walkability index is negatively correlated with the prevalence of hypertension. The fixed parameter model implies that a one-unit increase in walkability is associated with a 0·23% reduction in the prevalence of hypertension (Table 4). Despite the statistically significant reduction, the homogeneous fixed parameter model ignores the potential variations in the associations of walkability index. Compared to the average reduction of 0·23%, the quantile regression models show important non-linearities. Moreover, the potential reductions in hypertension due to an increase in walkability index are greater at the 10^{th}, 25^{th}, and 50^{th} percentile hypertension prevalence rates (Table 4 and Figure 4). In addition, the walkability associations vary significantly across the quantiles of hypertension. A unit increase in the walkability index was associated with a 0.31% reduction in hypertension prevalence at the 10th percentile of the prevalence of hypertension, which was 3.4 times the 0.09% decrease in hypertension prevalence seen at the 95th percentile. Regarding bicycle facilities, the provision of both on-street and off-street bike lanes was correlated with lower hypertension and the magnitude of reductions varied significantly across the quantiles of hypertension (Table 4 and Figure 4). Compared to the average reduction of 0·25% implied by the fixed parameter model, the potential reductions in hypertension due to each additional mile of off-street bike lane density ranged between 0·21% and 0·33% across the different percentiles of hypertension (Table 4). Neighborhoods with greater pedestrian-bicyclist fatal crashes had an on-average greater prevalence of hypertension, with significant variations across different quantiles (Figure 4).

Similar heterogeneous associations were observed regarding the links between the natural environment and neighborhood hypertension prevalence (Table 4). Depending on the quantile considered, each additional park was associated with a 0.17% to 0.25% reduction in hypertension prevalence. Social deprivation was positively correlated with prevalence of hypertension across all quantiles. The positive association of social deprivation was stronger in neighborhoods with high hypertension prevalence (> 95^{th} percentile). Compared to rural areas, the prevalence of hypertension is expectedly lower in metropolitan and micropolitan areas (Table 4).

3.2.2. Neighborhood-level Correlates of Obesity

The results in Table 5 show that the built environment characteristics are statistically significantly associated with obesity. The fixed parameter model implied a 0.25% reduction in obesity prevalence associated with each unit increase in neighborhood walkability. Simultaneous quantile regression models revealed considerable heterogeneity in walkability impacts across obesity quantiles (Table 5). For a unit increase in walkability index, the potential reduction in obesity at the 10^{th} percentile is around 1.8 times the reduction at the 95^{th} percentile of obesity distribution (0·32% at 10^{th} vs. 0·17% at 95^{th} percentile). Independent of the built/natural environment, bicyclist infrastructure was statistically significantly correlated with lower obesity prevalence, with relatively profound associations compared to natural environment impacts discussed below. Depending on obesity quantiles, a one-mile increase in buffered on-street bike facility per mile of roadway was correlated with a 0.07% to 0.16% reduction in obesity prevalence (Table 5 and Figure 5). Poor pedestrian-bicyclist safety was on-average associated with a greater prevalence of neighborhood obesity. The associations varied and were statistically significant across all quantiles considered, except for the 10^{th} percentile (Table 5). Neighborhood greenspace on average was negatively correlated with obesity – with significant variations across obesity quantiles (Figure 5). The number of total parks was positively correlated with obesity in the higher (95^{th}) percentiles (Figure 5). This finding does not imply causality and in fact, could be tracking other neighborhood-specific unobserved factors whose impacts could manifest through the (observed) built environment fabric (Ghimire et al. 2017, Wali et al. 2022a).

Similar to hypertension outcome, social deprivation was positively correlated with prevalence of obesity across all quantiles. Compared to rural neighborhoods, those in metropolitan, micropolitan, and small-town areas on-average exhibited lower levels of obesity. However, the magnitude of associations and statistical significance varied considerably across the quantiles (Table 5). Among the regions, neighborhoods in the South (especially the East South) had the highest prevalence of obesity. Like the hypertension outcome, considerable heterogeneity (both in magnitude and direction of associations) was found in the impacts of urban-rural and regional factors across the quantiles of obesity distribution (Table 5 and Figure 5). Figure 6 shows the predicted obesity and hypertension prevalence across the US regions – revealing highest and lowest prevalence of obesity and hypertension in the East South and West, respectively. Within regions, the prevalence rates varied widely across the quantiles [6] (Figure 6).

[6] As noted earlier, the prevalence of obesity and hypertension are based on small-area estimates with potential measurement errors as they are derived from individual-level survey data. Small area estimates are generally more precise than direct survey estimates (Ghosh and Rao 1994, Jia et al. 2004, Zhang et al. 2014, Kong and Zhang 2020). We considered the impacts of potential measurement errors by assessing the confidence intervals and standard errors of the estimated obesity and hypertension prevalence rates. The mean standard errors for predicted obesity and diabetes prevalence are 0.59% and 0.53%, respectively, with standard deviations of 0.18% and 0.16%. Thus, the CDC estimates are considerably precise. Additionally, considerable measurement errors (if present) mainly impact (statistical) efficiency (Greene 2018), i.e., the standard errors associated with beta coefficients would be biased and underestimated, leading to a type 1 error. Most estimable parameters across all quantiles in this study exhibit high statistical significance. Thus, the chance of type 1 error rendering our results statistically insignificant is very low due to the minimal measurement errors in CDC's predicted rates of obesity and hypertension.

TABLE 4. Heterogeneous Associations Between Hypertension and Environmental Features

Variable	LR	Quantile Regression									
		10th Percentile		25th Percentile		50th Percentile		75th Percentile		95th Percentile	
	β	β	[95% CI]	β	[95% CI]	β	[95% CI]	β	[95% CI]	β	[95% CI]
Outcome: Hypertension Prevalence (%)											
Built Environment											
Walkability Index	-0.23	-0.31	[-0.33,-0.3]	-0.27	[-0.28,-0.26]	-0.24	[-0.24,-0.23]	-0.18	[-0.19,-0.17]	-0.09	[-0.11,-0.06]
Bike Infrastructure & Safety											
Buffered off-street length density per mi.	-0.25	-0.33	[-0.4,-0.27]	-0.27	[-0.31,-0.23]	-0.24	[-0.27,-0.21]	-0.21	[-0.24,-0.18]	-0.29	[-0.35,-0.23]
Buffered on-street (bike lane) length density per mi.	-0.05	-0.06	[-0.09,-0.02]	-0.05	[-0.07,-0.03]	-0.04	[-0.06,-0.02]	-0.04	[-0.06,-0.02]	-0.02[a]	[-0.07,0.02]
Buffered 5-Year pedestrian & bicyclist fatal crash density per 100k pop	0.003	0.002	[0.0003,0.002]	0.003	[0.0008,0.005]	0.006	[0.004,0.008]	0.01	[0.009,0.01]	0.02	[0.01,0.02]
Natural Environment											
Buffered total park (any type) count	-0.17	-0.21	[-0.26,-0.16]	-0.2	[-0.23,-0.18]	-0.18	[-0.21,-0.15]	-0.18	[-0.21,-0.15]	-0.25	[-0.31,-0.18]
Social Deprivation / Vulnerability											
Social vulnerability index	0.11	0.084	[0.08,0.09]	0.085	[0.08,0.09]	0.09	[0.08,0.09]	0.1	[0.1,0.1]	0.14	[0.135,0.144]
Urban-Rural Continuum											
Rural	..	..	..	..	..	..	..	..	..	..	..
Metropolitan	-3.21	-3.38	[-3.65,-3.12]	-3.34	[-3.53,-3.14]	-3.5	[-3.7,-3.3]	-3.44	[-3.68,-3.2]	-2.17	[-2.6,-1.75]
Micropolitan	-2.33	-1.79	[-2.07,-1.5]	-1.71	[-1.92,-1.5]	-2.09	[-2.31,-1.88]	-2.47	[-2.75,-2.19]	-2.46	[-2.95,-1.96]
Small town	-1.41	-0.76	[-1.1,-0.42]	-0.75	[-0.99,-0.52]	-1.2	[-1.44,-0.97]	-1.64	[-1.94,-1.35]	-2.49	[-2.96,-2.01]
Regional Factors											
North East: New England	..	..	..	..	..	..	..	..	..	..	..
North East: Mid Atlantic	1.51	0.99	[0.67,1.3]	1.06	[0.89,1.22]	1.15	[0.97,1.33]	1.5	[1.33,1.68]	1.94	[1.48,2.41]

Notes: (··) is Not Applicable; LR is linear regression; All **β** estimates are statistically significant with $p < 0.05$ except those indicated by ([a]) with $p > 0.10$; N is sample size.

TABLE 4. (Continued). Heterogeneous Associations Between Hypertension and Environmental Features

Variable	LR	Quantile Regression									
		10th Percentile		25th Percentile		50th Percentile		75th Percentile		95th Percentile	
	β	β	[95% CI]	β	[95% CI]	β	[95% CI]	β	[95% CI]	β	[95% CI]
Regional Factors											
Mid West: East North	2.78	1.17	[0.88,1.47]	1.7	[1.51,1.89]	2.26	[2.06,2.46]	3.04	[2.85,3.23]	5.23	[4.74,5.71]
Mid West: West North	-0.2[a]	-1.57	[-1.9,-1.24]	-1.01	[-1.23,-0.79]	-0.32	[-0.56,-0.09]	0.48	[0.27,0.69]	1.58	[1.07,2.09]
South: South Atlantic	3.32	0.8	[0.5,1.1]	1.75	[1.57,1.93]	2.88	[2.67,3.09]	4.49	[4.24,4.73]	6.95	[6.5,7.41]
South: East South	6.98	5.16	[4.79,5.54]	6.06	[5.82,6.3]	6.62	[6.39,6.84]	7.53	[7.27,7.79]	9.22	[8.61,9.83]
South: West South	2.54	0.02[a]	[-0.32,0.36]	1.27	[1.05,1.5]	2.56	[2.33,2.8]	3.72	[3.5,3.94]	5.75	[5.22,6.27]
West: Mountain	-2.64	-4.12	[-4.46,-3.78]	-3.56	[-3.76,-3.36]	-3.01	[-3.23,-2.79]	-2.3	[-2.52,-2.08]	-0.12	[-0.71,0.46]
West: Pacific	-2.74	-2.8	[-3.1,-2.5]	-2.82	[-2.99,-2.65]	-2.91	[-3.12,-2.71]	-2.67	[-2.87,-2.47]	-1.55[a]	[-1.98,-1.12]
Intercept	34.11	32.71	[32.36,33.07]	33.78	[33.52,34.04]	35.14	[34.85,35.43]	35.56	[35.26,35.86]	35.02	[34.42,35.63]
Summary Statistics											
N	71,913	71,913		71,913		71,913		71,913		71,913	
Raw sum of deviations	..	85032.42		153764.8		200467.3		170309		61243.73	
Min sum of deviations	..	62643.9		110769.4		142004		120430.5		45097.84	
Pseudo R-squared	0.44	0.2633		0.2796		0.2916		0.2929		0.2636	
Total sum of squared errors	3756825.3	..		..		..		..		..	
Model sum of squared errors	1667859.8	..		..		..		..		..	

Notes: (··) is Not Applicable; LR is linear regression; All **β** estimates are statistically significant with $p < 0.05$ except those indicated by ([a]) with $p > 0.10$; N is sample size.

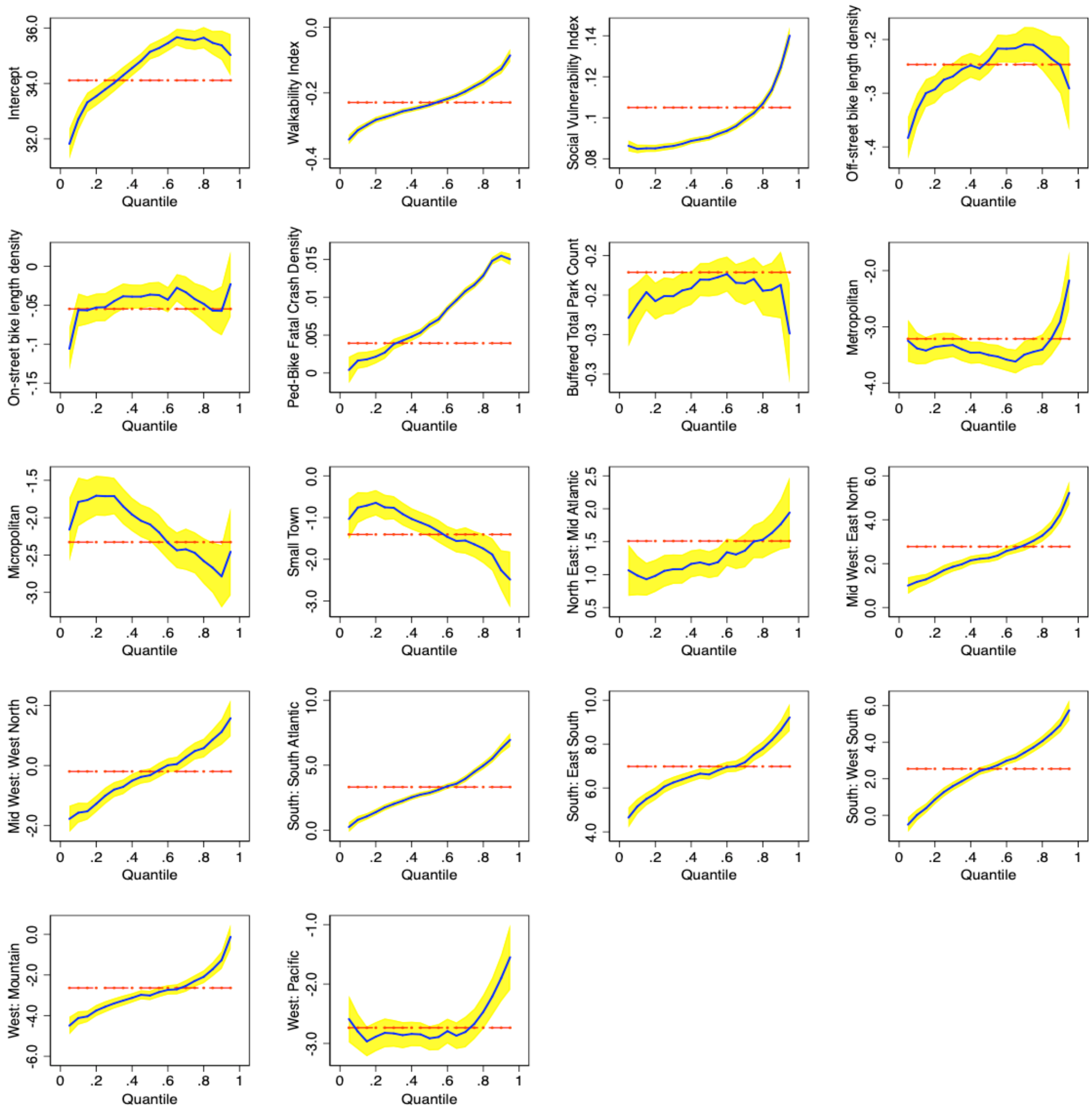

FIGURE 4. Heterogeneous Associations of Environmental Factors with Hypertension at Continuous Quantiles.

Notes: Figure shows associations of built & natural environment, bicyclist infrastructure, pedestrian-bicyclist safety, & regional factors with prevalence of hypertension. Red dashed line shows the estimate from linear model; Shaded region shows the quantile-specific 95% confidence intervals from simultaneous quantile regression.

TABLE 5. Heterogeneous Associations Between Obesity and Environmental Features

Variable	LR	Quantile Regression									
		10th Percentile		25th Percentile		50th Percentile		75th Percentile		95th Percentile	
	β	β	[95% CI]	β	[95% CI]	β	[95% CI]	β	[95% CI]	β	[95% CI]
Outcome: Obesity Prevalence (%)											
Built Environment											
Walkability Index	-0.25	-0.32	[-0.33,-0.31]	-0.30	[-0.31,-0.29]	-0.26	[-0.27,-0.25]	-0.22	[-0.23,-0.21]	-0.17	[-0.19,-0.15]
Bike Infrastructure & Safety											
Buffered off-street length density per mi.	-0.21	-0.27	[-0.31,-0.22]	-0.24	[-0.27,-0.2]	-0.22	[-0.25,-0.2]	-0.22	[-0.25,-0.2]	-0.23	[-0.29,-0.18]
Buffered on-street (bike lane) length density per mi.	-0.11	-0.09	[-0.12,-0.06]	-0.07	[-0.09,-0.05]	-0.10	[-0.12,-0.08]	-0.13	[-0.15,-0.11]	-0.16	[-0.19,-0.13]
Buffered 5-Year pedestrian & bicyclist fatal crash density per 100k pop	0.003	0.001[a]	[-0.0004,0.0022]	0.003	[0.002,0.005]	0.005	[0.003,0.01]	0.007	[0.006,0.008]	0.007	[0.005,0.009]
Natural Environment											
Buffered total park (any type) count	-0.04	-0.03	[-0.07,-0.0021]	-0.03	[-0.06,-0.01]	-0.06	[-0.08,-0.03]	-0.01[a]	[-0.04,0.02]	0.05	[0.01,0.1]
Social Deprivation / Vulnerability											
Social vulnerability index	0.15	0.125	[0.12,0.13]	0.132	[0.1305,0.1336]	0.142	[0.14,0.143]	0.152	[0.151,0.154]	0.175	[0.171,0.177]
Urban-Rural Continuum											
Rural	..	..	..	..	..	..	..	..	..	..	..
Metropolitan	-0.36	-1.14	[-1.38,-0.89]	-0.78	[-0.94,-0.62]	-0.26	[-0.41,-0.1]	0.03[a]	[-0.17,0.23]	0.1[a]	[-0.2,0.39]
Micropolitan	-0.1[a]	-0.35	[-0.63,-0.07]	-0.15[a]	[-0.33,0.04]	0.20	[0.02,0.38]	0.1[a]	[-0.12,0.32]	-0.23[a]	[-0.59,0.14]
Small town	-0.47	-0.31	[-0.6,-0.02]	-0.28	[-0.47,-0.08]	-0.31	[-0.52,-0.1]	-0.44	[-0.71,-0.17]	-0.59	[-0.96,-0.21]
Regional Factors											
North East: New England	..	..	..	..	..	..	..	..	..	..	..
North East: Mid Atlantic	1.76	1.26	[0.98,1.53]	1.62	[1.41,1.83]	1.92	[1.75,2.09]	2.20	[2.01,2.38]	2.66	[2.37,2.95]

Notes: (··) is Not Applicable; LR is linear regression; All **β** estimates are statistically significant with $p < 0.05$ except those indicated by ([a]) with $p > 0.10$; N is sample size.

TABLE 5. (Continued). Heterogeneous Associations Between Obesity and Environmental Features

Variable	Linear Regression	Quantile Regression									
		10th Percentile		25th Percentile		50th Percentile		75th Percentile		95th Percentile	
	β	β	[95% CI]	β	[95% CI]	β	[95% CI]	β	[95% CI]	β	[95% CI]
Regional Factors											
Mid West: East North	5.22	5.01	[4.79,5.22]	4.60	[4.41,4.79]	4.73	[4.56,4.9]	5.35	[5.14,5.55]	6.14	[5.85,6.43]
Mid West: West North	5.05	4.71	[4.42,5.01]	4.60	[4.38,4.82]	4.81	[4.6,5.02]	5.37	[5.13,5.61]	6.26	[5.94,6.58]
South: South Atlantic	2.58	2.47	[2.24,2.7]	2.17	[1.98,2.36]	2.12	[1.96,2.28]	2.62	[2.41,2.82]	3.71	[3.42,4]
South: East South	5.60	5.61	[5.36,5.85]	5.03	[4.8,5.25]	4.93	[4.73,5.13]	5.63	[5.4,5.86]	6.45	[6.04,6.86]
South: West South	5.00	5.52	[5.29,5.74]	5.00	[4.79,5.2]	4.55	[4.37,4.74]	4.52	[4.31,4.72]	4.80	[4.48,5.11]
West: Mountain	-0.25	-0.08[a]	[-0.37,0.22]	-0.23	[-0.46,-0.002]	-0.28	[-0.48,-0.09]	-0.33	[-0.54,-0.11]	-0.52	[-0.82,-0.22]
West: Pacific	-2.13	-1.88	[-2.14,-1.62]	-2.26	[-2.47,-2.05]	-2.30	[-2.48,-2.12]	-1.92	[-2.12,-1.73]	-1.52	[-1.81,-1.22]
Intercept	28.32	26.64	[26.26,27.02]	28.08	[27.8,28.35]	28.94	[28.7,29.17]	29.75	[29.48,30.02]	31.00	[30.54,31.46]
Summary Statistics											
N	71,913	71,913		71,913		71,913		71,913		71,913	
Raw sum of deviations	..	83049.09		154815		196992.7		158250.2		53973.3	
Min sum of deviations	..	50706.31		92642.5		118241.4		95792.4		32154.2	
Pseudo R-squared	0.66	0.3894		0.4016		0.3998		0.3947		0.4043	
Total sum of squared errors	3380060.5	..		..		..		..		..	
Model sum of squared errors	2099237.5	..		..		..		..		..	

Notes: (··) is Not Applicable; LR is linear regression; All **β** estimates are statistically significant with $p < 0.05$ except those indicated by ([a]) with $p > 0.10$; N is sample size.

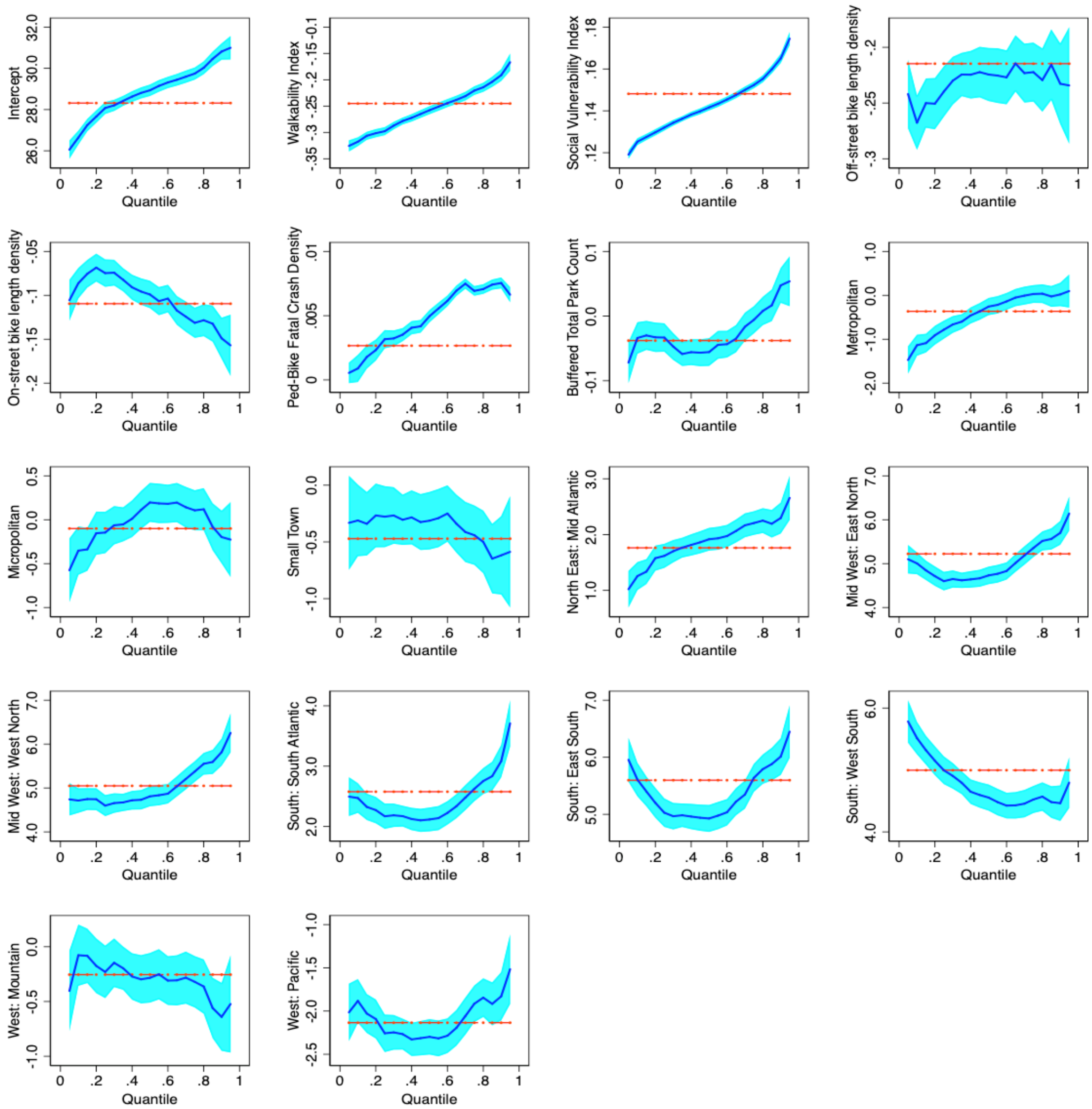

FIGURE 5. Heterogeneous Associations of Environmental Factors with Obesity at Continuous Quantiles.

Notes: Figure shows associations of built & natural environment, bicyclist infrastructure, pedestrian-bicyclist safety, & regional factors with prevalence of obesity. Red dashed line shows the estimate from linear model; Shaded region shows the quantile-specific 95% confidence intervals from quantile regression.

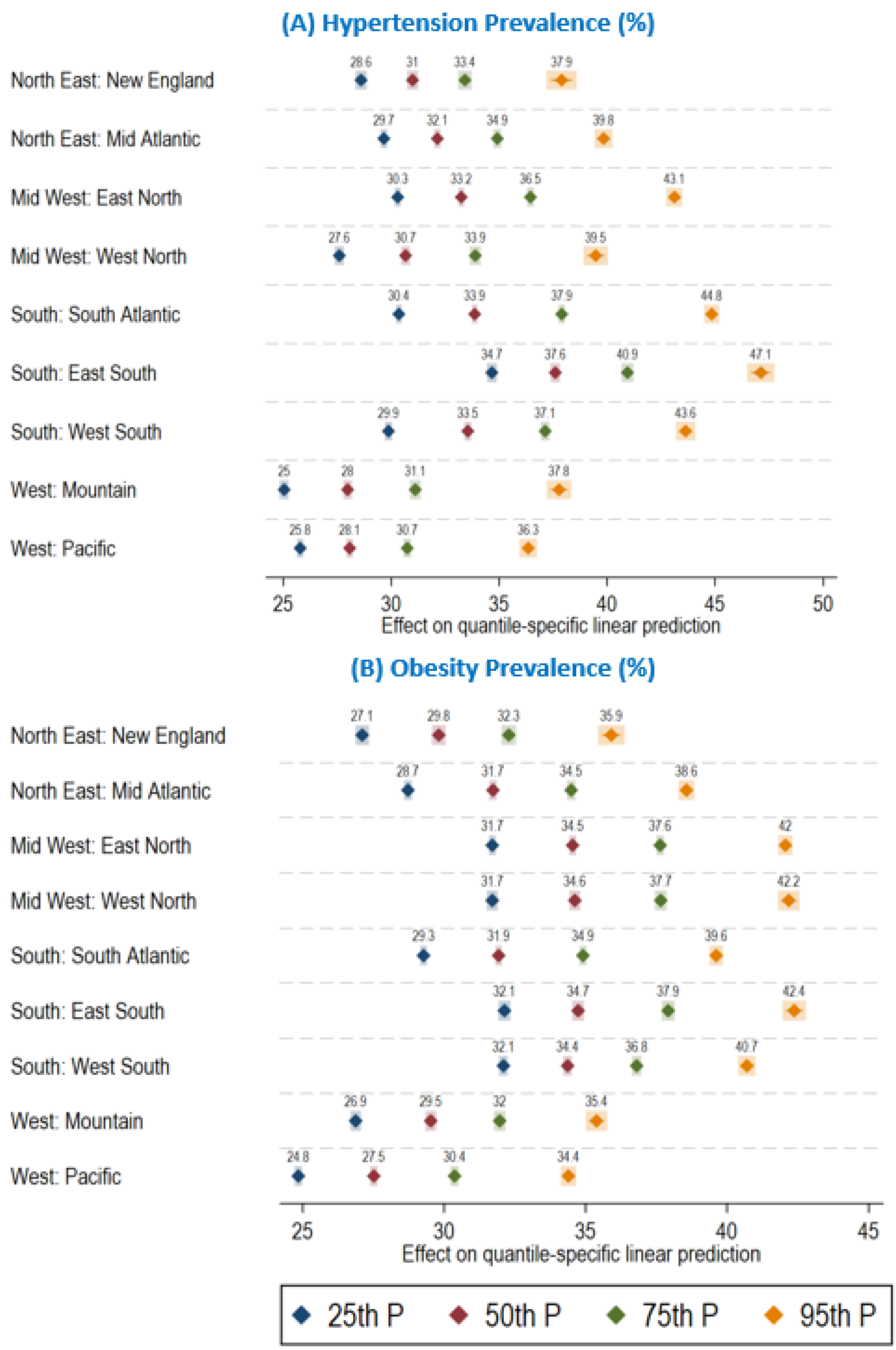

FIGURE 6. Predicted Hypertension and Obesity Prevalence Rates Across US Regions.
Notes: Quantile-specific point estimates and 95% confidence intervals are shown. 25th P, 50th P, 75th P, and 95th P indicate the respective percentiles. The estimates are based on the models presented in Table 4 and Table 5 and control for built and natural environment features, pedestrian-bicyclist infrastructure, and urban-rural indicators. The predicted values are calculated by setting regional indicators at specific values (corresponding to each of 9 US census regions) and integrating over sample/census-tract values of the remaining covariates.

4. DISCUSSION

This study quantified the associations of objectively-assessed built/natural environment and bicyclist infrastructure design features with neighborhood-level hypertension and obesity prevalence – an issue of major public health concern (WHO 2021, WHO 2024). As discussed in the earlier section, the heterogeneous linkages are estimated to be strong and statistically significant[7]. Our findings on the associations of environmental factors with hypertension and obesity agree with individual-level studies documenting the positive health impacts of walkable and greener environments[8] (Lopez-Zetina et al. 2006, Chandrabose et al. 2019, Adhikari et al. 2021, Avila-Palencia et al. 2022). More walkable neighborhoods with greenspace support physical activity and active travel (Adhikari et al. 2020), which are associated with lowered risks of hypertension and obesity (Fox and Hillsdon 2007, Diaz et al. 2017). Unlike previous studies, our results unveil significant heterogeneity in the impacts of built and natural environment features on hypertension and obesity prevalence that could be an outgrowth of systematic variations in neighborhood-level observed and a range of unobserved factors.

Independent of the effects of walkability and social deprivation, our findings also highlight the potential of bicyclist-supportive infrastructure in reducing neighborhood hypertension and obesity prevalence. Poor levels of pedestrian-bicyclist safety were correlated with a greater prevalence of obesity and hypertension. Neighborhoods with more pedestrian-bicyclist crashes (lower safety) may lack infrastructure for safer walking and biking (Saha et al. 2020, Wali and Frank 2024) which can hinder active transportation (Sallis et al. 2012). Lower active transportation-related physical activity is generally associated with higher obesity and hypertension levels (Sallis et al. 2012, Diaz and Shimbo 2013). However, the relationship between walkability and pedestrian-bicyclist safety is complicated as noted elsewhere (Wali and Frank 2024). Previous studies have reported a positive correlation between social vulnerability and chronic disease prevalence (Aubé-Maurice et al. 2012, Vinikoor-Imler et al. 2012, Angier et al. 2020). Our findings extend the literature by demonstrating heterogeneous associations of social

[7] Overall, the heterogeneous associations are quantified quite precisely, as all the β estimates are highly significant. While the R-squared statistics shown are helpful to understand predictive power, our focus is on evaluating individual β estimates as R-squared statistics do not have a substantive meaning in an explanatory (as opposed to predictive) context (Figueiredo Filho et al. 2011, Ozili 2023). Having said this, the R-squared statistics in our study are sizeable considering the nationwide scale of the present study, ranging from 0.26 to 0.44 for hypertension and 0.38 to 0.66 for obesity. It is not uncommon to observe R-squared values below 0.2 in the travel behavior and social science literatures (Hensher and Sullivan 2003, Buehler 2012, Salon 2015, Domenech-Abella et al. 2020, Li et al. 2020).

[8] The results of our study should not be interpreted at the individual level because of the ecological study design. However, numerous individual-level studies have found that the physical characteristics of the environment impact health outcomes (Renalds et al. 2010, Malambo et al. 2016), with walkability generally associated with lower chronic disease risk (Koohsari et al. 2020). Therefore, a broader comparison of ecological findings to individual-level studies can help assess the behavioral validity of ecological findings. Doing so does not diminish the importance of ecological analyses in understanding the determinants of neighborhood-level disease prevalence, which as noted earlier, is important for developing community-based nonpharmacologic interventions (Economos and Irish-Hauser 2007, Heath et al. 2012, Mensah et al. 2018, HHS 2020).

vulnerability with obesity and hypertension prevalence. Importantly, the impacts of social deprivation were more pronounced in neighborhoods with greater hypertension and obesity prevalence. Regarding spatial factors, the considerable heterogeneity associated with urban-rural and regional factors is likely capturing the role of macroscopic space-time factors that often vary significantly across large geographies, and which are unobserved in the data at hand. Compared to samples restricted to specific localities (e.g., cities) (Donovan et al. 2021), the utilization of a nationwide sample with significant variability in health outcomes and environmental exposures enhances the external validity of the results.

4.1. Study Implications

The study presents a substantive and methodological contribution to scholarship in the field with practical implications. From a substantive viewpoint, a key gap in the literature has been the lack of nationwide evidence concerning the links between the built/natural environment and neighborhood-level chronic disease prevalence. Previous studies harnessing data from the CDC's 500 Cities (predecessor of PLACES) have focused on social disparities in chronic disease (Fitzpatrick et al. 2018, Liu et al. 2018a, Liu et al. 2018b, Quick et al. 2020). The present study demonstrated the value of built and natural environment features in quantifying the variability in neighborhood-level hypertension and obesity prevalence after controlling for social deprivation. Contrary to the approach of a few published studies using 500 Cities data discussed earlier, we intentionally excluded neighborhood-level socio-demographic factors as additional correlates since PLACES estimates are already derived from individual-level models with sociodemographic factors as independent variables (CDC 2020b, Kong and Zhang 2020). The redundant inclusion of demographic factors was omitted from the models to avoid endogeneity issues. Our results demonstrate that the built and natural environment features are independently predicting PLACES outcomes beyond demographic and socioeconomic factors. Being physically active is among the key strategies identified in The Surgeon General's Call to Action to Control Hypertension (HHS 2020). More walkable and greener environments provide greater opportunities to engage in active travel and physical activity (Mytton et al. 2012, Rundle et al. 2016). Our results support the need to explore the inclusion of built and natural environment features in the development of future versions of PLACES. As municipalities increasingly focus on developing large-scale programs and interventions to combat hypertension and obesity (TFAH 2018), it seems justified and rational that the hypertension and obesity estimates in PLACES be adjusted for the environmental factors increasingly known to significantly impact health (Renalds et al. 2010, Bird et al. 2018, Wali et al. 2022b). Deductively, among other factors, chronic diseases result from complex interactions between lifestyle factors (e.g., diet), travel behaviors (e.g., physical activity), and the environment. The built environment represents a broad spectrum of social and physical elements that formulate community structure (French et al. 2014) and could influence chronic disease outcomes. To this end, future versions of PLACES could benefit from the inclusion of built and natural environment variables in estimating hypertension and obesity outcomes. Including these factors can also improve the perceived validity of PLACES models by accounting for additional factors that are becoming well supported by numerous peer-reviewed studies designed to predict chronic disease outcomes. The fact that these additional environmental factors are modifiable and subject to policy priorities makes them far more important (TFAH 2018, HHS 2020). This type of evidence further creates accountability within transportation investment prioritization and land use decision-making processes.

Methodologically, the study unveiled heterogeneous associations of built/natural environment and bicycle facilities with hypertension and obesity quantiles. Findings show that the average trends quantified by homogenous fixed parameter models (reflected by statistically significant coefficients in the expected direction) could be incomplete and biased, and under the often-untested homogeneity assumption, can hinder quantification of policy-relevant heterogeneous impacts of built and natural environments. For example, the potential reductions in hypertension due to improvements in walkability and/or bicycle facilities are greater at the lower quantiles, with the magnitude of reductions decreasing at higher quantiles of hypertension. This implies that improvement in walkability may lead to greatest gains in neighborhoods that have lower (than average) hypertension rates. Neighborhoods with substantially higher rates are typically places with extremely high concentrations of underserved disadvantaged residents (Wilper et al. 2008). These communities usually exhibit other major structural issues (e.g., spatial segregation, socioeconomic disparities) which are social environment barriers that need to be addressed for effects of the built and natural environment features to even matter (Wali 2023). To this end, the heterogeneous associations identified in this study provide a basis for targeted place-based interventions that can support the environmental justice and healthy community goals of the Justice40 initiative (White House 2022b).

4.2. Limitations & Future Research

Our study has some limitations. Causal inferences should be avoided given the correlational nature of the current study. As with all ecological study designs, the insights presented may not necessarily transfer to the individual level. However, the results were in the expected direction and agree with individual-level studies which increase our confidence in the ecological findings. We did not explicitly quantify the impacts of several factors (e.g., medical resources, attitudes, etc.) due to data unavailability. However, the study framework takes into consideration the latent impacts of such unobserved factors, which are tracked as unobserved heterogeneity and separated from factors we are able to observe. This study provides evidence that supports consideration for the inclusion of built and natural environment features in future iterations of the PLACES database. Compared to the ecological framework used here, future studies can compare the two analytical approaches (demographics alone vs. demographics and built/natural environmental factors) by harnessing consistent individual-level health outcome data and comparing small area estimate results obtained from the two sets of individual-level models. Finally, future studies may extend the framework presented in this study to assess environmental impacts on the neighborhood prevalence of other chronic diseases available in the PLACES database, including cancer, coronary heart disease, and stroke.

5. CONCLUSION

To our knowledge, this is the first study to harness data from PLACES with a focus on examining the heterogeneous associations of built/natural environment and bike infrastructure factors with neighborhood hypertension and obesity prevalence after controlling for social deprivation and other spatial unobserved factors. Findings from the study add to the existing body of literature documenting how the built and natural environment impacts neighborhood-level hypertension/obesity outcomes. Results from this study document significant hypertension and obesity relationships with environmental features not currently accounted for in the PLACES small-area chronic disease estimates. Independent of social deprivation, walkability, provision of green space, and bicycle facilities were correlated with lower neighborhood prevalence of hypertension and obesity. The study results may be used to inform how environmental factors are incorporated into future iterations of national disease prevalence data programs (e.g., PLACES) and can also be used by decision-makers to aid in improving effective planning policy to better target infrastructure investments to promote public health. This is particularly timely given the potential for major infrastructure spending from the federal level to be undertaken in the near future (White House 2022b, White House 2022a). Characterized by significant heterogeneity, the potential reductions in chronic disease varied significantly across the quantiles of neighborhood-level hypertension and obesity rates. Such high-resolution insights can help identify locations where the greatest gains can be made - enabling the development and targeting of place-based built and natural environment interventions for hypertension and obesity control.

6. DATA SHARING

The authors welcome correspondence from anyone interested in learning more about the datasets used in this study. Health outcome data are extracted from the publicly available PLACES database from the US Centers for Disease Control and Prevention. The environmental data are extracted from the RWJF-supported National Environmental Database. After publication of this study, study protocols, data dictionary, and census-tract level integrated health and environmental data may be made available after signing a data sharing and use agreement.

7. APPENDIX A

TABLE A1. Geographic Resolution, Time Frame, and Data Sources of Study Variables.

Variable	Geographic Resolution	Data Year	Data Source
Chronic Disease Prevalence (%)			
High Blood Pressure / Hypertension	Census Tract	2017[a]	US CDC PLACES Database (2020 Release)
Obesity	Census Tract	2018	US CDC PLACES Database (2020 Release)
Social Vulnerability / Deprivation			
Social Vulnerability Index (SVI)	Census Tract	2014-2018	US CDC SVI (2019 Release); Agency for Toxic Substances and Disease Registry, U.S. Center for Disease Control & Prevention (CDC)
Built Environment			
Walkability Index (on scale 0 to 100)	CBG; Aggregated to census tract	2017-2020	National Environmental Database (NED) (2020 Release); Urban Design 4 Health and Robert Wood Johnson Foundation.
Residential density (housing units / acre)		2018	NED (2020 Release); American Community Survey 5-Year Estimates, U.S. Census Bureau
Street network intersection density (count / sq. km.)		2018	NED (2020 Release); HERE Maps NAVSTREETS
Employment mix (on scale from 0 to 1)		2017	NED (2020 Release); Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES), U.S. Census Bureau
Access to transit (# of stops)		2020	NED (2020 Release); General Transit Feed Specification (GTFS), Transit Authorities
Vehicle Miles Travelled	Census Tract	2019	NED (2020 Release); Location Affordability Index, U.S. Department of Transportation (DOT); U.S. Department of Housing & Urban Development (HUD)
Bike Infrastructure & Safety			
Buffered off-street length density per mi·	CBG; Aggregated to census tract	2021	CalTrans; Open Street Map (OSM)
Buffered on-street (bike lane) length density per mi·		2021	
Buffered 5-Year pedestrian fatal crash density per 100k population		2015-2019	Fatality Analysis Reporting System (FARS), U.S. National Highway Traffic Safety Administration (NHTSA)
Buffered 5-Year bicyclist fatal crash density per 100k population		2015-2019	
Natural Environment			
Buffered total park (any size) count	CBG; Aggregated to census tract	2020	Protected Areas Database (PAD-US), U.S. Geological Survey (USGS); OSM Park Inventory Source.
Buffered total park area (any size)			
Buffered tree canopy coverage (%)		2016	National Land Cover Database (NLCD), U.S. Geological Survey (USGS)
Urban-Rural Continuum	Same	2010	Rural-Urban Commuting Area (RUCA) Codes by US Department of Agriculture
Regional Factors	Same	2010	Census Regions and Divisions of the United States by US Census

Notes: CBG is census block group; (a) The high blood pressure estimates in the 2020 PLACES Release are based on the 2017 Behavioral Risk Factor Surveillance Survey (BRFSS) since the question on high blood pressure is only asked every other year in the survey; US CDC is US Centers for Disease Control and Prevention.

TABLE A2. Cross-tabulation of High Blood Pressure and Obesity Prevalence

Prevalence of high blood pressure	Prevalence of Obesity			Total
	Low	Medium	High	
Low	10,523	7,205	392	18,120
	58.07	39.76	2.16	100
	57.63	20.11	2.2	25.2
Medium	6,792	22,538	6,498	35,828
	18.96	**62.91**	18.14	100
	37.19	62.91	36.45	49.82
High	946	6,084	10,935	17,965
	5.27	33.87	**60.87**	100
	5.18	16.98	61.35	24.98
Total	18,261	35,827	17,825	71,913
	25.39	49.82	24.79	100
	100	100	100	100
Goodness of Fit Measures				
Pearson Chi2 (4) = 2700; Pr = 0.000				
Gamma = 0.7530; ASE = 0.003				
Kendall's Tau-b = 0.5161; ASE = 0.003				

Notes: Categories are defined as follows: (1) Low – prevalence ≤ 25th percentile; (2) Medium – prevalence > 25th percentile & ≤ 75th percentile; and (3) High – prevalence > 75th percentile. For each combination of obesity and hypertension prevalence, three statistics are provided. The first statistic is the frequency count; the second statistic (light grey cell) is the row percentage summing up to 100% going across the table; the third statistic (dark grey cell) is the column percentage summing to 100% going down the table.

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