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Redefining Walkability to Capture Safety: Investing in Pedestrian, Bike, and Street Level Design Features to Make it Safe to Walk and Bike

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ABSTRACT

Walkable neighborhoods provide significant sustainability, health, and motorized user safety benefits. Far less consideration is given to the potential pedestrian/bicyclist safety-related implications of macro-level walkability. Making it desirable to walk and bike without providing the proper physical environment to make it safe is clearly problematic. This study assessed the links between neighborhood walkability and pedestrian/bicyclist traffic fatalities across metropolitan areas in the U.S. We integrated and harnessed geocoded data on pedestrian/bicyclist and all mode traffic fatalities, travel behavior exposures (use of sedentary and active travel modes), sociodemographic, and control variables. Associations of pedestrian/bicyclist traffic fatality rates with walkability characteristics were estimated using multilevel Tobit models with treatment for hierarchical unobserved regional and state variations. Walkability index (mixed land use, street intersection density, and transit accessibility) was positively correlated with pedestrian/bicyclist fatality rates after adjusting for travel exposures, sociodemographic controls, and regional and state-level unobserved variations. A unit increase in the walkability index was associated with a 4.9% increase (95% CI: 4.2%, 5.7%) in pedestrian/bicyclist fatality rates. Conversely, the walkability index was negatively correlated with total or all-mode fatality rates. The positive association between walkability and pedestrian/bicyclist fatality rates appeared robust in different sensitivity analyses. Despite non-linearities, neighborhoods with greater population using active travel modes for commute had on-average higher pedestrian/bicyclist fatality rates. The reverse was true for neighborhoods with greater teleworking population. Neighborhoods with greater prevalence of black, low-income, and younger adults had on-average higher pedestrian/bicyclist fatality rates. Results emphasize the need to develop new conceptual definitions of walkability that consider safety within the built environments. Our results highlight the importance of understanding how pedestrian/bicyclist supportive design can be used to maximize the positive health benefits of walkability while reducing the risk of pedestrian/bicyclist deaths. Findings also suggest the need to enhance existing walkability assessment techniques (indices) to predict and simulate how different investments impact pedestrian/bicyclist safety. Incorporation of objective pedestrian/bicyclist safety in walkability assessments can assist practitioners to simultaneously improve health while minimizing safety risks to vulnerable road users.

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Keywords: Neighborhood urban design; walkability, pedestrian/bicyclist safety.

1. INTRODUCTION

Road safety is a major public health issue with 1.35 million people killed each year on roadways worldwide (WHO 2018). As a leading cause of death for people aged 5-29, road traffic fatalities disproportionately impact pedestrians and bicyclists (pedestrian/bicyclist) (WHO 2018). Pedestrians/bicyclists are the most vulnerable road users since they lack the protection offered by enclosed vehicles. More than half of the people killed in road crashes worldwide were pedestrians, bicyclists, and motorcyclists (WHO 2018). In the U.S., pedestrian fatalities increased by around 46% in the last decade compared to a 5% increase in all other traffic fatalities (GHSA 2019). With an unacceptable rise in pedestrian/bicyclist fatalities, over 6,000 pedestrians and 850 bicyclists are killed each year in the U.S. comprising around 19 percent of all road traffic fatalities (NHTSA 2019). An additional 76,000 pedestrians and 49,000 bicyclists are injured each year.

Due to the disproportionate safety burden borne by vulnerable road users, pedestrian/bicyclist safety has become an increasingly critical component of road safety management and is a key public health priority. The built environment serves as a key focal point that can be retrofitted to improve pedestrian/bicyclist safety outcomes (Stoker et al. 2015, Thompson et al. 2020, Ahmad et al. 2021). Walkable neighborhoods have sustainability and public health related benefits – namely, support for active travel (Frank et al. 2005, Cao et al. 2006, Saelens and Handy 2008, Handy et al. 2014), better mental health (Wang et al. 2019, Guzman et al. 2021, Asiamah et al. 2022), and lower morbidity and mortality from chronic (Frank et al. 2003, Jackson 2003, Rundle et al. 2009, Sallis et al. 2012, Wali et al. 2022) and infectious diseases (Adlakha and Sallis 2021, Wali and Frank 2021, Alidadi and Sharifi 2022, Wali 2023). In addition, more walkable neighborhoods offer significant motorized user safety benefits noting the previous exception when it comes to exposure to local levels of air pollution which was also found to be positively correlated with walkability (Marshall et al. 2009). Past ecological studies suggest lower automobile injury/fatality rates in more compact and walkable neighborhoods[1] (Dumbaugh and Rae 2009, Marshall and Garrick 2011, Moeinaddini et al. 2014, Yeo et al. 2015, Ewing et al. 2016, Quistberg et al. 2022). This is expected since walkable neighborhoods help reduce motorized travel speed, traffic volumes, and unsafe behaviors (Ewing and Dumbaugh 2009, Stoker et al. 2015).

Compared to motorized user safety, far less consideration is given to the potential pedestrian/bicyclist safety-related implications of neighborhood walkability. Pedestrian/bicyclist safety concerns have long been recognized (Jackson 2003) and central to the development of innovative community programs including Complete Streets/Vision Zero (Moreland-Russell et al. 2013, Cushing et al. 2016) and Safe Routes to School (Moreland-Russell et al. 2013). However, empirical evidence on the relationship between neighborhood-level walkability and pedestrian/bicyclist safety is extremely scarce. The studies that have examined the links between built environment and pedestrian/bicyclist fatalities have been limited to a single city or region or alternatively used coarse geographic units such as whole counties. The body of research in this area has shown conflicting results (Ewing et al. 2003, Ukkusuri et al. 2011, Mohan et al. 2017, Osama et al. 2020, Yin and Zhang 2021). Some researchers found a negative association between urban compactness and pedestrian fatalities using spatially aggregate county/city level data (Ewing et al. 2003, Mohan et al. 2017). Other researchers found a positive association between aspects of walkability/bikeability and pedestrian/bicyclist crashes using more granular (e.g., Traffic Analysis Zone) data for a single city (Ukkusuri et al. 2011, Osama et al. 2020, Yin and Zhang 2021). To our knowledge, no study has evaluated neighborhood-level built environment in relation to pedestrian/bicyclist fatalities using a diverse nationwide sample of neighborhoods across the U.S[2].

[1] This study assesses walkability in relation to pedestrian/bicyclist safety. Walkability is operationalized differently from the separate construct of bike-ability (Arellana et al. 2020). However, we note that the traditional “3D” (design, diversity, density) walkability measures are predictive of both walking and biking behaviors (Frank et al. 2003, Saelens et al. 2003).

[2] Following an ecological design, this study focuses on neighborhood-level pedestrian/bicyclist safety in the U.S. in relation to fine-grained objectively measured walkability characteristics. We searched Web of Science, PubMed, Transportation Research International Documentation, and Google Scholar for articles published from inception till March 28, 2023, analyzing pedestrian/bicyclist traffic fatality outcomes in the U.S. in relation to urban design and built environment characteristics, using the keywords: ("built environment" or "walkability" or "urban design") AND ("road traffic mortality" or "traffic fatalities" or "pedestrian" or "bicyclist" or "cyclist”). Although we found several ecological studies examining automobile injury/fatality rates in relation to urban design, the evidence on potential pedestrian/bicyclist safety implications of neighborhood urban design was scarce. The few ecological studies that examined the links between built environment and pedestrian (bicyclist) fatalities and are synthesized above were limited to a single location with limited variation and generalizability or used highly aggregate (county-level) data. We did not find any ecological study evaluating fine-grained neighborhood-level built environment features in relation to pedestrian and bicyclist traffic fatalities using a diverse nationwide sample of U.S. neighborhoods. Several studies have examined associations of built environment with pedestrian/bicyclist safety outcomes at the individual-level (Rothman et al. 2014, Xin et al. 2017) or at the road segment- or intersection-level (Miranda-Moreno et al. 2011, Dai and Jaworski 2016, Mukherjee and Mitra 2022). Such individual-level studies are outside the scope of the present work given our focus on neighborhood-level pedestrian/bicyclist safety outcomes.

This study examines neighborhood-level pedestrian/bicyclist fatality rates in the U.S. and analyzes its links with neighborhood-level walkability characteristics including urban compactness, design, land-use mix, and transit accessibility. Neighborhood-level total fatality rates (including automobile fatality rates) are also examined for comparative purposes. Findings are discussed in light of the need to develop new conceptual definitions of walkability that consider the need for safety within built and natural environments. Results along these lines are critical to guide pedestrian/bicyclist safety-oriented design and maximize the favorable health benefits that walkability can produce (such as improving physical activity (Frank et al. 2006, Yang et al. 2022) and chronic disease (Sallis et al. 2016, Howell and Booth 2022, Wali et al. 2022)) while lowering the risk of pedestrian/bicyclist fatalities.

2. METHODS

2.1. Study Design

This study follows an ecological study design where environmental factors are captured and measured in a similar manner to which they are experienced. Our sample consists of all census tracts in metropolitan areas across the U.S. (N = 59,038 census tracts) housing over 83% of the U.S. population. The present study focuses on neighborhoods in metropolitan areas as safety outcomes and walkability levels vary significantly across urban and rural areas. Geocoded data from multiple sources are integrated to develop a unique database of pedestrian/bicyclist fatalities, urban form/built environment, travel exposures, and control variables. Census tracts provided a consistent nationwide geographic scale with sufficient spatial resolution to capture variations in urban form and safety outcomes across neighborhoods.

2.1.1. Fatality Data

Five years (2015-2019) data on pedestrian/bicyclist and total fatalities (all road traffic fatalities by all modes including motorized users, motorcyclists, pedestrian/bicyclists, and other modes) were obtained from the Fatality Analysis Reporting System (FARS) (FARS 2021). Maintained by the National Highway Traffic Safety Administration (NHTSA), FARS is a nationwide road safety census providing the American public and decision makers yearly data on fatal injuries in road crashes. A total of 34,085 pedestrian/bicyclist fatalities were considered – 87% (29,661) of which occurred in metropolitan neighborhoods. Over 72% of total fatalities (122,072 out of 167,451) occurred in metro neighborhoods. The crash locations (latitude and longitude) were geocoded to census tracts nationwide. Dependent variables including pedestrian/bicyclist and total fatality rates (all-mode fatality rate) per 100,000 population were computed by dividing census tract level fatality counts over census-tract population multiplied by 100,000. The use of population as the denominator in the calculation of fatality or mortality rates is a standard practice in the safety literature (Ewing et al. 2003, Yeo et al. 2015, Ewing et al. 2016). Other denominators such as normalized area was also used in sensitivity analyses reported later. As a standardized national database, data from FARS are routinely used in the traffic safety literature to examine the correlates of objectively-assessed all-mode and mode-specific traffic fatalities at individual and ecological levels (Marshall and Garrick 2011, Hanna et al. 2012, Lee et al. 2018). Previous US-based studies that examined built environment and road safety synthesized earlier were also based on fatality data from FARS (Ewing et al. 2003, Marshall and Garrick 2011, Ewing et al. 2016).

2.1.2. Built Environment & Travel Exposures

Data on neighborhood-level built environment features including detailed spatial characteristics of urban design (street connectivity), land-use (diversity), and transit accessibility were incorporated. Obtained from the recently updated version 3.0 of Smart Location Database (SLD) by U.S. Environmental Protection Agency (Chapman et al. 2021), the measures included pedestrian-oriented street intersection density, 8-tier employment entropy, 5-tier employment and residential entropy, and proximity to transit stops. These are previously used measures in the literature examining how the built environment predicts health behaviors (e.g., walking, biking) (James et al. 2017, Mooney et al. 2020) and health outcomes including chronic (Watson et al. 2020, Makhlouf et al. 2022) and infectious diseases (Wali and Frank 2021). To address spatial multicollinearity arising between built environment features (Frank et al. 2010), we harnessed a composite neighborhood-level national walkability index (NWI) combining the above measures into a single index. Meeting the unmet demand for evidence-based tools, the U.S. EPA's NWI serves as a national tool to consistently compare neighborhoods for their potential to support active travel and health (Thomas and Reyes 2021). Several studies have documented the use of the U.S. EPA's NWI as a viable walkability measure predicting travel and health outcomes (James et al. 2017, Watson et al. 2020, Wali and Frank 2021). A detailed overview of the walkability index and underlying built environment measures is provided in the *Supplementary Materials* section (Appendix A).

Road safety outcomes are determined by the underlying travel exposures (Pei et al. 2012, Mannering et al. 2020). As a key travel exposure metric, data on neighborhood-level household vehicle miles traveled (VMT) were used. These data are derived from a model developed by Bureau of Transportation Statistics using data from the Federal Highway Administration's National Household Travel Survey (NHTS) and U.S. Census Bureau's American Community Survey (ACS) (BTS 2017). Integrating NHTS and ACS data addresses the issue of NHTS not being well-suited for small geographical areas due to its limited sample sizes (BTS 2017). The BTS VMT data is the only resource that is publicly available nationwide at the census tract level. We acknowledge that these data may undercount neighborhood VMT contributed by non-residents. For methodology and validation, see BTS (2017) (BTS 2017). Besides the number of residents and VMT in a neighborhood; pedestrian/bicyclist safety outcomes also depend on the amount of travel conducted through active travel modes (Qin and Ivan 2001). Travel-mode specific (including transit, biking, walking, and teleworking) neighborhood commute data were retrieved from the 2019 "Detailed Tables" in American Community Survey (ACS). Neighborhood-level population counts for five-years (2015-2019) were obtained to calculate the percentages of population using active travel modes (walk, bike, transit) for work commute. We note that mode choice for commute travel may not be a perfect proxy for total travel mode split. However, we were limited by the information captured in the U.S. Census Bureau's American Community Survey, which only provides consistent nationwide data on travel-mode specific commute patterns at the neighborhood (census tract) level. Additionally, the methodological framework (outlined later) accounts for potential omitted variable bias that may arise due to the use of imperfect travel mode-split data.

2.1.3. Demographic & Travel Behavior Factors

Data on key neighborhood-level sociodemographic characteristics were used as controls. Population counts were retrieved from the 2015-2019 ACS "Detailed Tables" to calculate neighborhood sociodemographic measures (as population percentages) including gender, age, race, education, income, employment, and vehicle ownership. Data on income and vehicle availability are at the household-level; these variables indicate the percentage of households belonging to different income and vehicle ownership groups. Variables measuring travel behavior exposures described above were also used as controls. To capture variations across U.S. regions, all neighborhoods (census tracts) were classified into nine U.S. regions using the Census Bureau Regions and Divisions classification scheme (Census 2010).

2.2. Statistical Methodology

Detailed exposition of the modeling framework is provided in *Supplementary Materials* (Appendix A). Associations of outcome variables (pedestrian/bicyclist fatality rates) with the built environment, travel exposures, and controls were modeled using a hierarchical three-level Tobit modeling framework. Traffic fatality rate is a standardized measure of roadway safety that considers the number of accidents normalized to exposure, such as the number of traffic fatalities per 100,000 population (AASHTO 2010). Additionally, instead of traditional fatality counts, using exposure-based fatality rates as the outcome variable is appealing as it provides a standardized measure of the relative safety of census tracts that can be interpreted more easily (Anastasopoulos et al. 2008). The traffic fatality rates are continuous but exhibit a preponderance of zeroes (i.e., zero pedestrian/bicyclist fatality rates) (Supplementary Figures 1 and 2, Appendix A, and discussed later). Thus, a latent-variable based Tobit framework was used in a "corner-solution" setting to treat the rest of the (non-zero) log-transformed distribution differently than the spikes at zero (Greene 2018, Wali et al. 2019). Hierarchical random effects at the regional and state levels were included to capture the impacts of unobserved factors on pedestrian/bicyclist and total fatality rates (see *Appendix A* for details on the modeling framework). Previous studies have successfully used Tobit framework for modeling crash rates at a more microscopic level, including at road segment or intersection levels (Anastasopoulos et al. 2008, Xu et al. 2014, Zeng et al. 2017). With a key focus on built environment impacts, all the models adjusted for travel exposures, demographic, and socioeconomic factors. The walkability index was modeled both as a continuous and quartile-based categorical variable. Non-linear associations of travel exposures were explored and modeled through quadratic terms. A natural logarithmic transformation of the outcome variables was used to deal with the high skewness. To handle zero pedestrian/bicyclist fatality rates in the log transformation, we added a value of one to all observations and subsequently calculated the logarithm as log $(fatality\ rate + 1)$. For details, see *Supplementary Materials* (Appendix A).

The above framework was also used to model all-mode fatality rates for comparative purposes. To enable a more meaningful interpretation, individual-level marginal effects averaged across the sample were computed. The marginal effects (MEs) pertain to the actual response outcomes including both censored and uncensored observations – reflecting a corner-solution implementation of a Tobit modeling framework (Greene 2018, Wali et al. 2019). We conducted sensitivity analyses to examine the robustness of the findings from the main analyses. Sensitivity analyses included repeating the main analyses (1) with pedestrian/bicyclist fatalities normalized by census tract developed area as the outcome variable, (2) separately for nine U.S. regions, and (3) removing census tracts with zero pedestrian/bicyclist fatalities. All the descriptive and inferential analyses were conducted in R and Stata (version 15.1).

3. RESULTS

3.1. Descriptive Analysis

Figure 1 shows the geocoded locations of all pedestrian/bicyclist fatalities nationwide. Significant variations existed in the nationwide distribution of pedestrian/bicyclist fatality rates across all census tracts (Figure 2). Complete data on the outcome, exposure, and control variables were available for 59,038 metropolitan census tracts (neighborhoods) nationwide. On average, there were 11·28 pedestrian/bicyclist fatalities per 100,000 population (Table 1) in the metropolitan neighborhoods across the U.S. Around 67% and 32% of metropolitan neighborhoods had zero pedestrian/bicyclist and total fatalities, respectively – revealing "left censoring" in the distributions of safety outcomes nationwide (Supplementary Figures 1 and 2, *Appendix A*). Built environment characteristics also exhibited substantial variations. A wide range of employment and household entropy, static 8-tier employment entropy, pedestrian-oriented intersection density, and distance to nearest transit stop was observed (Table 1). Ranging between 1 and 19·83, the mean national walkability index score was 10·37 indicating "average" walkability. The national walkability index was positively correlated with log transformed pedestrian/bicyclist fatality rates (Pearson correlation = 0·0958, p-value = 0·000) whereas the reverse was true for log transformed total fatality rates (Pearson correlation = -0·2282, p-value = 0·000) (Supplementary Table 1, *Appendix A*). Regarding travel exposures, the average household produced 37·83 vehicle miles daily. Around 9·75% of the neighborhood population used active travel modes (walk, bike, transit) for commute travel. Around 5·11% of the neighborhood population participated in teleworking. Regarding control variables, the distributions of sociodemographic factors and neighborhoods across the nine U.S. regions were reasonable (Table 1). Most of the metropolitan neighborhoods were in South Atlantic (19·8%), Pacific (16·3%), and Mid Atlantic (15·3%) regions.

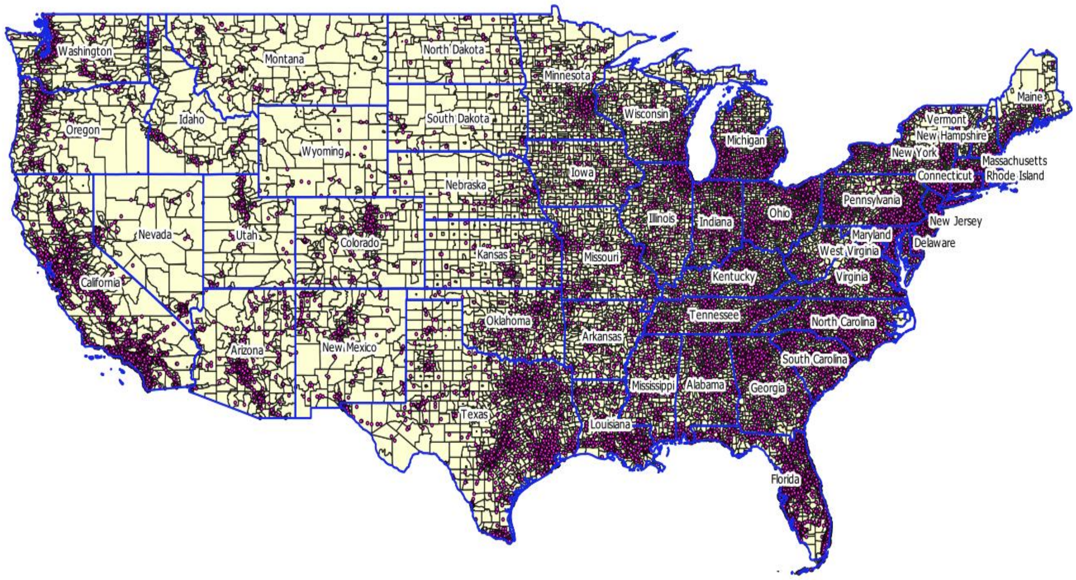

FIGURE 1. Geocoded Locations of Pedestrian/Bicyclist Fatalities Nationwide.
Notes: Each dot represents a pedestrian/bicyclist fatality; Black lines show boundaries of census tracts; Blue lines show state boundaries; Alaska and Hawaii not shown.

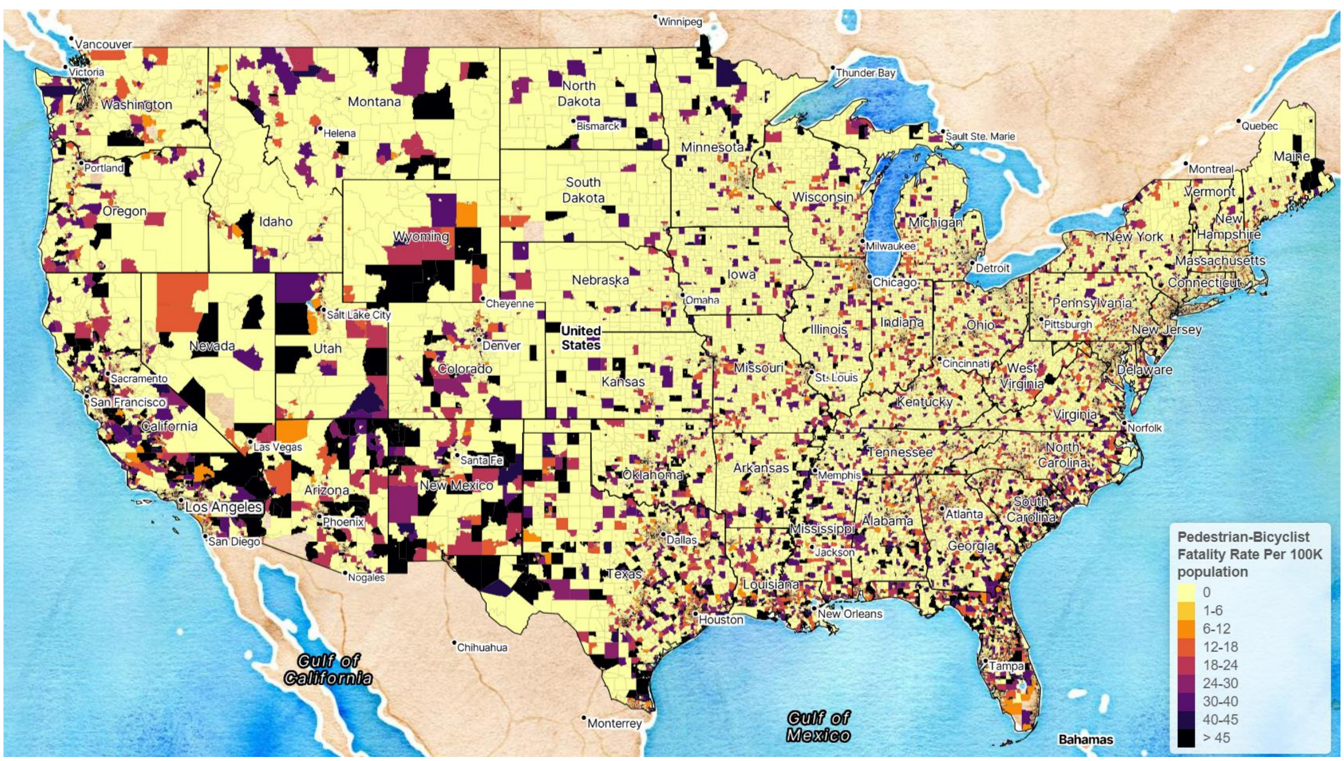

FIGURE 2. Distribution of Pedestrian/Bicyclist Fatality Rate (No. of Fatalities Per 100,000 Population) Across All Census-Tracts.
Notes: Alaska and Hawaii not shown.

TABLE 1. Descriptive Statistics of Key Variables

Category	Variable	Mean	SD	Range
Outcomes	Pedestrian/bicyclist fatalities	0·5	0·95	[0, 29]
	Pedestrian/bicyclist fatality rate / 100K population	11·28	33·51	[0, 2702·70]
Built Environment	Employment & household entropy	0·5	0·16	[0, 0·98]
	Static 8-tier employment entropy	0·69	0·14	[0, 1]
	Street intersection density (auto-oriented intersections eliminated) (count / sq. km.)	86·57	71·79	[0, 1422·45]
	Distance to nearest transit stop (meters)	1019·82	555·44	[0, 1500]
	National Walkability Index	10·37	3·9	[1, 19·83]
Exposure	Population	4628·79	2403·15	[37, 72041]
	Average household daily vehicle miles traveled (VMT)	37·83	13·18	[0, 77·65]
	VMT missing dummy*	0·02	0·13	[0, 1]
Travel Exposure (% of population using …. for commute travel)	Transit	6·34	12·53	[0, 91·82]
	Biking	0·61	1·59	[0, 46·81]
	Walking	2·8	5·57	[0, 100]
	Active (transit, biking, walking) modes	9·75	15·65	[0, 100]
	Teleworking	5·11	3·99	[0, 76·28]
Demographics (%)	Female	50·99	4·05	[0·52, 96·56]
	Age: 18-29 years	16·77	9·23	[0, 99·57]
	Age: 30-39 years	13·44	4·54	[0, 54·92]
	Black	15·14	22·59	[0, 100]
	White	69·47	25·6	[0, 100]
	Asian	5·9	9·93	[0, 93·76]
	Education: Less than high school	12·41	10·65	[0, 81·65]
	Education: Graduate	12·9	10·65	[0, 76·32]
	Low income [a]	32·62	17·34	[0, 100]
	Low-middle income [a]	24·71	7·87	[0, 74·28]
	High-middle income [a]	12·45	4·92	[0, 47·94]
	High income [a]	30·22	18·88	[0, 100]
	Unemployed	3·57	2·45	[0, 29·10]
	No-vehicle households	9·84	13·08	[0, 100]
Regional Factors (%)	North East: New England		4·78	
	North East: Mid Atlantic		15·33	
	Mid West: East North		15·8	
	Mid West: West North		5·46	
	South: South Atlantic		19·83	
	South: East South		4·81	
	South: West South		10·77	
	West: Mountain		6·92	
	West: Pacific		16·31	

Notes: SD is standard deviation; N = 59,040 except travel exposure variables (N = 59,038); (*) VMT data was missing for 1,007 census tracts (1.7%). Dummy variable coding was used to incorporate neighborhoods with missing VMT data and to estimate the effect of missing VMT, i.e., the missing VMT values were replaced with 0 and a new binary variable was created coded as 1 if VMT was replaced with 0 (missing VMT) and 0 otherwise. Both variables were used as controls in the subsequent analyses. (a) low income (less than $40,000 / year), low-middle income ($40,000 – $74,999), high-middle income ($75,000 - $100,000), and high income (greater than $100,000).

3.2. Modeling Results

Results of hierarchical Tobit models linking pedestrian/bicyclist fatality rates with built environment are shown in Table 2. Results for both continuous walkability index and quartiles of walkability index as key covariates are shown (Model 1 and 2 in Table 2). For comparative purposes, the results of hierarchical Tobit models for total fatality rate outcomes with continuous walkability index and walkability index quartiles as key independent variables are shown in the appendix (Supplementary Table 2). All models accounted for travel exposures, control variables, and regional and state-specific random effects. The adjusted β estimates are hard to interpret given the latent utility structure of the Tobit model. For log-transformed pedestrian/bicyclist fatality rate outcomes, the marginal effects shown in Table 2 (when multiplied by 100) indicate the % change in pedestrian/bicyclist fatality rates with a unit increase in continuous variable or a switch from 0 to 1 (for binary variables).

The walkability index was positively correlated with pedestrian/bicyclist fatality rates after adjusting for travel exposures, sociodemographic controls, and regional and state-level unobserved variations. A one unit increase in the walkability index was associated with a 4.9% increase (CI: 4.2%, 5.7%) in pedestrian/bicyclist fatality rates (Model 1 in Table 2). Quartile-based walkability index revealed non-linear, yet proportional, relationships across walkability quartiles (Model 2). Compared to neighborhoods with walkability ≤ 25th percentile, the pedestrian/bicyclist fatality rates in neighborhoods with walkability in the second, third, and fourth quartiles were higher by 10.2%, 20.7%, and 43.2%, respectively (Table 2). Conversely, walkability index was negatively correlated with total fatality rates adjusting for travel exposures, controls, and unobserved variations across regions and states (Model 3 and 4 in Supplementary Table 2, Appendix A). A one unit increase in the walkability index was correlated with a 0.8% decrease in the total fatality rate (Model 3, Supplementary Table 2, Appendix A). For total fatality rates, quartile-based walkability index revealed non-linear and non-proportional relationships across walkability quartiles (Model 4, Supplementary Table 2, Appendix A). Compared to neighborhoods with lowest walkability, those with walkability index in quartile 2, quartile 3, and quartile 4 had total fatality rates lower by 48.5%, 51.4%, and 29.4% respectively (Model 4, Supplementary Table 2, Appendix A). Figure 3 shows the predicted marginal effects of walkability quartiles on pedestrian/bicyclist and total fatality rates – revealing statistically significant associations, in the opposite direction, of walkability index with pedestrian/bicyclist and total fatality outcomes.

As expected, travel behavior exposures (population counts using active travel modes) exhibited statistically significant associations with pedestrian/bicyclist fatality rates. We base the discussion of travel behavior exposures on the results of continuous walkability model (Model 1) since it resulted in best-fit with lowest AIC compared to quartile-based walkability model (Model 2) (Table 2). For otherwise similar neighborhoods (i.e., everything else being same or equal), those with higher daily vehicle miles travelled had higher pedestrian/bicyclist fatality rates. A nonlinear relationship existed between neighborhood-level prevalence of active travel for commute and pedestrian/bicyclist fatality rates. Reflecting a trigger effect (Figure 4), the pedestrian/bicyclist fatality rates were significantly higher in neighborhoods with greater population using active travel modes for commute travel. As expected, neighborhoods with greater teleworking population had lower pedestrian/bicyclist fatality rates (Table 2). Sociodemographic factors revealed potential disparities with greater pedestrian/bicyclist fatality rates in neighborhoods with greater prevalence of black and low-income individuals. Despite non-linearity (Figure 4), the average association of younger individuals (18-29 years old) with pedestrian/bicyclist fatality rate was positive (see MEs in Table 2).

TABLE 2. Multilevel Tobit Models for Pedestrian/Bicyclist Fatality Rate Outcome

Variable	Model 1				Model 2			
	β	95% CI	ME	95% CI	β	95% CI	ME	95% CI
Built Environment								
Walkability Index (WI)	0·152	[0·136, 0·168]	0·049	[0·042, 0·057]	··	··	··	··
WI: Quartile 1 (base)	··	··	··	··	··	··	··	··
WI: Quartile 2	··	··	··	··	0·359	[0·222, 0·496]	0·102	[0·062, 0·142]
WI: Quartile 3	··	··	··	··	0·698	[0·547, 0·85]	0·207	[0·158, 0·257]
WI: Quartile 4	··	··	··	··	1·331	[1·161, 1·502]	0·432	[0·361, 0·502]
Behavioral Exposure (% of commuters)								
Active travel	0·036	[0·019, 0·053]			0·042	[0·025, 0·059]		
[Active travel]^2	-0·001	[-0·002, -0·001]	0·007 [a]	[0·003, 0·01]	-0·002	[-0·002, -0·0009]	0·008 [a]	[0·004, 0·012]
[Active travel]^3	1.24E-05	[7.4E-06, 1.7E-05]			1·35E-05	[8·6E-06, 1·8E-05]		
Teleworking	-0·014	[-0·026, -0·001]	-0·004	[-0·009, -0·0004]	-0·015	[-0·027, -0·003]	-0·005 [a]	[-0·009, -0·001]
Average household daily vehicle miles traveled (VMT)	0·05	[0·044, 0·056]	0·016	[0·014, 0·019]	0·043	[0·037, 0·049]	0·014	[0·011, 0·017]
VMT missing dummy	1·533	[1·153, 1·913]	---	---	1·35	[0·97, 1·73]	---	---
Sociodemographic Factors (% of population)								
Female	-0·034	[-0·044, -0·024]	-0·011	[-0·014, -0·007]	-0·033	[-0·043, -0·023]	-0·011	[-0·014, -0·007]
Black	0·008	[0·006, 0·011]	0·003	[0·002, 0·003]	0·008	[0·006, 0·011]	0·003	[0·002, 0·004]
Graduate	-0·028	[-0·034, -0·023]	-0·009	[-0·011, -0·007]	-0·026	[-0·032, -0·02]	-0·008	[-0·011, -0·006]
Low income	0·042	[0·038, 0·046]	0·014	[0·012, 0·016]	0·041	[0·037, 0·045]	0·013	[0·011, 0·015]
Age: 18-29 years	0·055	[0·042, 0·068]	0·008 [a]	[0·006, 0·011]	0·06	[0·048, 0·073]	0·009 [a]	[0·007, 0·012]
[Age: 18-29 years]^2	-0·001	[-0·001, -0·0006]			-0·001	[-0·001, -0·0007]		
Constant	-5·445	[-6·268, -4·622]	··	··	-4·4	[-5·206, -3·593]	··	··
Heterogeneity								
Variance: Regional level (constant)	0·295	[0·093, 0·933]	··	··	0·293	[0·092, 0·929]	··	··
Variance: State level (constant)	0·376	[0·230, 0·614]	··	··	0·376	[0·230, 0·615]	··	··
Variance: Neighborhood level (constant	15·898	[15·519, 16·286]	··	··	15·931	[15·551, 16·320]	··	··

Notes: Response outcome is log (pedestrian/bicyclist fatality rate + 1); pedestrian/bicyclist fatality rate equals # of pedestrian/bicyclist fatalities per 100,000 population; (··) is Not Applicable; (---) indicate no marginal effect computed for policy-irrelevant variable such as VMT missing dummy variable; CI is confidence interval; ME is average marginal effect; Models 1 and 2 include continuous walkability index and quartiles of walkability index, respectively; The four walkability index (WI) quartiles correspond to: (min, WI_{25P}], (WI_{25P}, WI_{50P}], (WI_{50P}, WI_{75P}], (WI_{75P}, max] – where "P" indicates the corresponding percentiles of walkability index; N = 59,038 census tracts; Uncensored N = 18,953; Left-censored N = 40,085; Log-likelihood at convergence and Akaike Information Criterion equal -73,674.80 and 147,383.60 (for Model 1) and -73,712.43 and 147,462 (for Model 2), respectively; Hierarchical grouping information for Model 1 and 2: Number of regions = 9; N per region [minimum, average, maximum] = [2,821, 6,559.8, 11,709]; Number of states = 51; N per state [minimum, average, maximum] = [39, 1,157.6, 7,474]; Both multi-level Tobit models include hierarchical region and state-specific random effects; All the statistics shown have p-values < 0·005 except teleworking in continuous walkability model (Model 1) with p = 0·028. The average marginal effects (MEs) are obtained from multilevel Tobit utility functions pertaining to the actual response outcome including both censored and uncensored observations, i.e., true corner-solution setting. Since the dependent variables are log-transformed, multiplying the MEs by 100 indicates the % change in pedestrian/bicyclist fatality rates with a unit increase in continuous variable or a switch from 0 to 1 (for binary variables). (a) The average marginal effects shown reflect the combined average impact on pedestrian/bicyclist fatality rates, considering both linear and polynomial terms for relevant variables such as age and active travel. This is because the derivative in calculation of average marginal effect is with respect to age and not the squared term. In fact, [Age: 18-29 years]^2 cannot change independent of [Age: 18-29 years]. Predicted non-linear impacts across the entire range of age and active travel values can be seen in Figure 4.

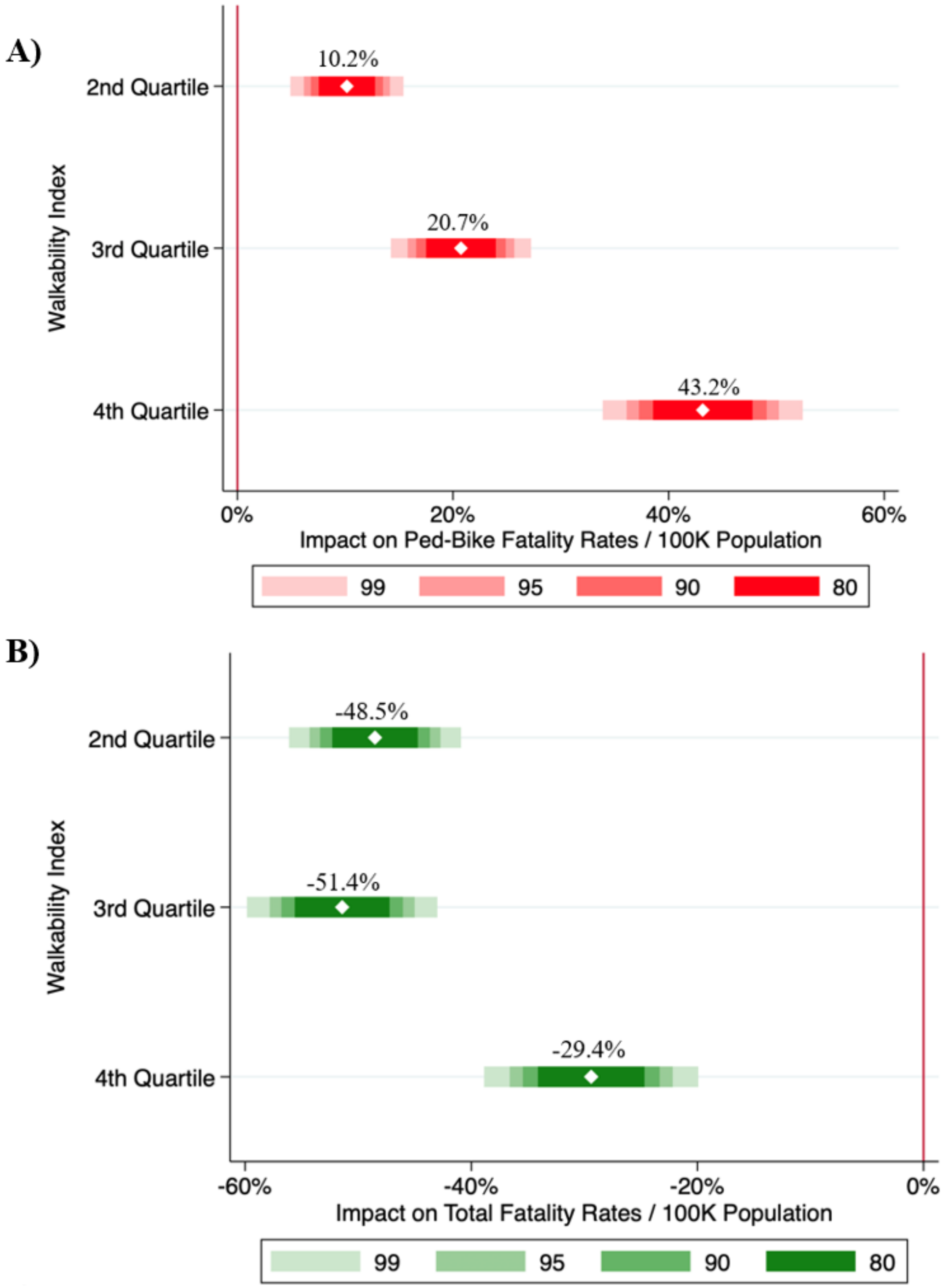

FIGURE 3. Pedestrian/Bicyclist and Total Fatality Rates Across Walkability Quartiles.
Notes: A and B show the predicted percent change (averaged across neighborhoods) in pedestrian/bicyclist and total fatality rates across walkability quartiles (relative to the first quartile of walkability index, i.e., least walkable), respectively. Predicted marginal effects in A and B are obtained from the estimates of hierarchical Tobit models – Model 2 in Table 2 and Model 4 in Supplementary Table 2 (Appendix A), respectively. The predicted average marginal effects are obtained from multilevel Tobit utility functions pertaining to the actual response outcome including both censored and uncensored observations, i.e., true corner-solution setting.

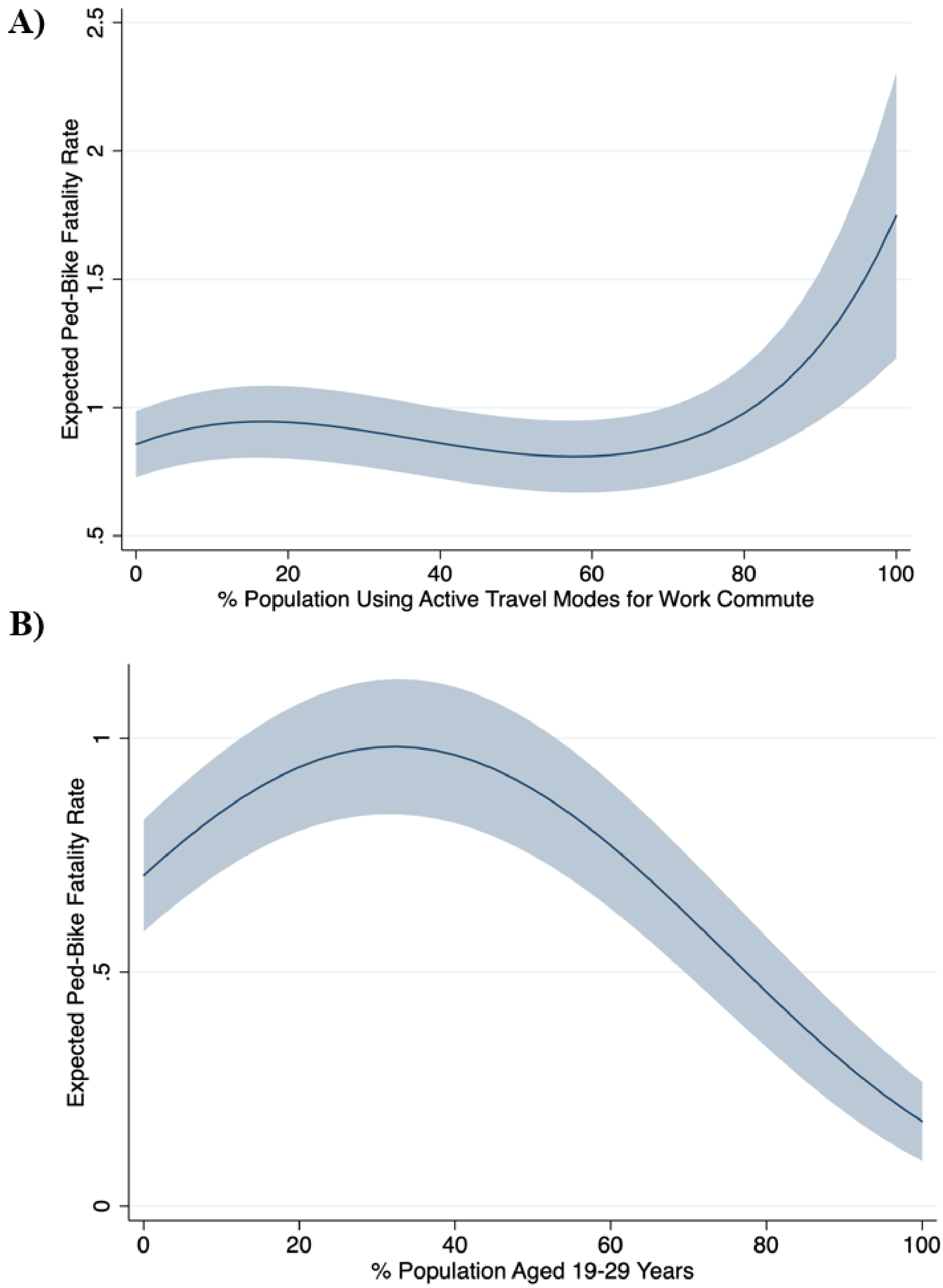

FIGURE 4. Expected Pedestrian/Bicyclist Fatality Rates.

Notes: A and B show the predicted pedestrian/bicyclist fatality rates across percent population using active travel modes (walk, bike, transit) for work commute and percent population aged 19-29 years, respectively. Predicted marginal effects in A and B are obtained from the estimates of best-fit hierarchical Tobit model (Model 1 in Table 2). Predictions are obtained from multilevel Tobit utility functions pertaining to the actual response outcome including both censored and uncensored observations, i.e., true corner-solution setting.

The positive association between walkability and pedestrian/bicyclist fatality rates appeared robust in different sensitivity analyses. The direction of association between walkability and pedestrian/bicyclist fatality rates did not change in sensitivity analyses that excluded neighborhoods with zero pedestrian/bicyclist fatalities and in multilevel hierarchical models with pedestrian/bicyclist fatalities normalized by census-tract developed area (instead of normalization by population) (Supplementary Table 3, Appendix A). While the magnitude of associations varied, the direction of (positive) association did not change and remained statistically significant in segmented models for the nine U.S. regions (Supplementary Table 3, Appendix A). We assessed pedestrian/bicyclist fatality rates per vehicle miles traveled as a response outcome, which was also positively associated with walkability (results not shown).

4. DISCUSSION

This study is among the first to examine the links between neighborhood-level measures of walkability and pedestrian/bicyclist fatality rates at a national scale. Empirical evidence on the association between neighborhood walkability and pedestrian/bicyclist safety at a national scale with the wide variation it provides is scarce. The use of higher resolution data is critical to adequately capture the substantial local variations in built environment and safety outcomes that are obscured when highly aggregate (county/city level) data are used. We assembled a unique database integrating geocoded data from multiple sources to test how the built environment associates with neighborhood pedestrian/bicyclist fatality rates controlling for travel exposures, demographics, and other exogenous control variables. We note that in our data (based on NHTSA's database) pedestrian fatalities (~ 6000 each year) are more common than bicyclist fatalities (~ 850 each year). Thus, the results presented throughout are dominated by trends in pedestrian fatalities.

In hierarchical multilevel adjusted Tobit models, more walkable neighborhoods (as indicated by higher walkability index) had significantly higher pedestrian/bicyclist fatality rates after adjusting for travel behavior exposures, demographic factors, regional, and state-level unobserved variations. This is an important finding which contradicts previous findings reporting a negative relationship between urban compactness and pedestrian fatality rates using county or city-level data (Ewing et al. 2003, Mohan et al. 2017). Our comparative analysis of total fatality rates revealed a negative relationship between walkability and all-mode fatality rates – which is in agreement with results from aggregate (county/city-level) data (Ewing et al. 2003, Marshall and Garrick 2011, Moeinaddini et al. 2014, Ewing et al. 2016, Quistberg et al. 2022). The negative relationship between total neighborhood fatality rates and walkability is intuitive since vehicle speed is among the biggest causes of road traffic fatalities (Khattak et al. 2003, Hussain et al. 2019, Wali et al. 2020), and more compact and walkable neighborhoods discourage higher travel speeds (Litman 2008), thus lowering total fatality rates.

However, from a pedestrian/bicyclist safety perspective, it is also critical to minimize potential conflicts between nonmotorized and motorized users - a key surrogate safety measure since non-motorized users lack the protection offered by enclosed vehicles (Islam et al. 2014). The lowered speeds in more compact/walkable neighborhoods that are "safer" for vehicles are not safe enough for pedestrians/bicyclists. For example, the statutory speed limit (established by U.S. State legislatures and which can vary across U.S. States) in residential districts is generally 25 mph (~40 kph) (FHWA 2017) and drivers often break low urban speed limits (Tapp et al. 2016). Previous research suggests that a low speed (e.g., 30 kph) considered otherwise safer might not be a "safe" speed for pedestrians hit by vehicles (Kröyer 2015). Likewise, evidence shows that severe injury risk for a pedestrian hit by a vehicle is at least 50% at an impact speed of around 30 mph (Tefft 2013). While more walkable places should reduce travel speeds, the macroscopic built environment characteristics widely used in the literature as measures of greater walkability do not necessarily lower, and could in fact increase, potential conflicts between motorized and non-motorized users. For example, a more heterogenous mixed land use pattern increases proximity to destinations and creates demand for walking and cycling as does higher intersection density with smaller blocks offering a more connected road network and route directness through connected streets. This land use pattern is often coupled with street design standards intended to prioritize vehicle flow and the resulting environment is both highly conducive to generating demand for active transportation yet contains conflict hotspots between motorized and non-motorized users (Schneider et al. 2004, Ma et al. 2018). With a greater exposure to potential conflicts, pedestrians and bicyclists can suffer serious harm even in collisions with speeds that are generally considered safer for motorized users. Notwithstanding our findings controlling for vehicle miles traveled (VMT), we note that the above findings relate to the potential direct connection between urban design and pedestrian/bicyclist safety (e.g., in terms of conflicts between motorized and non-motorized users), as opposed to the indirect link between urban design and pedestrian safety through VMT (Stoker et al. 2015).

From a safety viewpoint, our results also highlight the need to consider pedestrian environment features in walkability assessments. Macroscopic walkability measures (such as density, design, diversity, etc.) do not fully capture microscale pedestrian environment that supports safer mobility of pedestrians and bicyclists (Rodríguez et al. 2009, Cain et al. 2014, Steinmetz-Wood et al. 2020, Wali et al. 2022). Pedestrian environment features such as presence of traffic control devices, traffic calming measures, (Zebra) crosswalks, curb ramps, sidewalks, and dedicated bikeways determine the location and separation between pedestrian/bicyclist and vehicular movements which determines the potential for conflicts, injury, and even death. The association between microscale pedestrian features and objectively measured macro-level walkability is positive but weak-to-moderate at best (Adams et al. 2009, Cain et al. 2014, Adams et al. 2022). The correlation between total microscale score (composite measure of eight safety-relevant pedestrian environment features) and macro-level walkability index was about 0.30 (Adams et al. 2022). These results suggest that in many places, macro walkability (land use and transportation network design) do not have a supportive pedestrian and cycling environment promoting pedestrian/bicyclist safety.

The importance of reducing auto-oriented design and promoting walkable neighborhoods with greater density, diversity, and transit accessibility is well established (Cervero and Kockelman 1997, Frank et al. 2003, Miranda-Moreno et al. 2011). This legacy has persisted over decades to structure residential areas around local streets (Hess 2009) and away from urban arterials that create the 'flow and place' conundrum of contrasting rationalities to maintain traffic flows and develop a sense of place (Patton 2007). Structuring "live, work, and play" areas away from arterials is necessary but not necessarily sufficient for vulnerable road user safety. Pedestrian activities are significantly lower around arterials (Miranda-Moreno et al. 2011), with most activities occurring in immediate (home, work, and play) environments (Sevtsuk 2021) with more local or non-arterial roads. Therefore, it seems imperative to reduce the likelihood of vehicle-pedestrian conflicts even in local environments. This is because the speeds on local roads are not necessarily safer for pedestrians/bicyclists (as discussed before). The provision of ped-bike infrastructure can thus reduce conflicts by separating pedestrian and vehicular movements to lower the risk of unsafe outcomes. Besides health and environmental considerations, this is important from a social equity viewpoint (Litman 2023), i.e., ensuring that motorized users do not endanger non-drivers.

Collectively, our findings on the pedestrian/bicyclist safety impacts of macro-level walkability align with the need to develop new conceptual definitions of walkability that consider the need for safety within built and natural environments (Tobin et al. 2022). Our findings emphasize the need to learn more about how pedestrian design elements can be used to maximize the favorable health benefits that walkability can produce while lowering the risk of pedestrian/bicyclist fatalities.

4.1. Limitations & Future Research

Strengths of our study include the use of diverse nationwide data sources with greater spatial resolution across a diverse spectrum of urban neighborhoods in the U.S. The use of advanced econometric models revealed clear insights about the links between walkability and pedestrian/bicyclist safety and which did not meaningfully change in sensitivity analyses. However, there are certain limitations to the present study. The analysis is cross-sectional in nature, and which precludes causal insights. We only analyzed pedestrian/bicyclist and total fatalities which are relatively rare safety outcomes (Lord et al. 2021). Injury data are not available in FARS and can only be obtained from individual states in the U.S. Future studies should assess the associations between walkability and pedestrian/bicyclist injury outcomes at a national level, which could be different from the associations for fatality outcomes observed in this study. The present study analyzed the relationship between U.S. EPA's national walkability index with pedestrian/bicyclist safety. Such indices are widely used in literature to assess the sustainable travel and health benefits of urban design and transport investments. Future studies should assess other walkability indices used in the literature and can expand the results by analyzing the individual components within the walkability index which can provide deeper insights. Future research efforts examining the empirical relationships between pedestrian environment features and safety outcomes can provide critical policy and transportation investment insights. Evidence suggests that pedestrian environment features are systematically lacking in lower income and underserved communities (Bereitschaft 2017, Steinmetz-Wood et al. 2020). There is also a need to compare mortality rates across demographic sub-groups to understand potential heterogeneity in the associations between walkability and mortality.

5. CONCLUSIONS

Traffic fatalities are a major public health issue with the safety burden disproportionately borne by pedestrians and bicyclists. Walkable neighborhoods provide sustainability, health, and motorized user safety benefits. However, far less consideration is given to the potential pedestrian/bicyclist safety-related implications of walkability. To our knowledge, this is the first study to examine neighborhood-level associations of built environment and walkability characteristics with pedestrian/bicyclist fatality rates in the U.S.

Interestingly, the current study was conducted by researchers who have focused their careers on the many benefits of walkability. Our findings suggest that more walkable neighborhoods (such as those with more mixed land-use, greater intersection density, and better transit accessibility) may not be necessarily safer for pedestrians and bicyclists. With pedestrian/bicyclist safety a major public health issue in the U.S. and globally, the new findings highlight the unmet need to develop, operationalize, and validate new conceptual definitions of walkability that consider safety within built and natural environments.

Making it desirable to walk and bike without providing the proper physical environment to make it safe is clearly problematic. Findings do not diminish the documented health benefits offered by walkable neighborhoods. Rather, they point to the critical need to incorporate pedestrian design features within the definition of "walkability" that support safer pedestrian/bicyclist mobility in traditional walkability assessments largely characterized by macroscopic built environment measures (such as density, design, and diversity). To this end, there is a continued need to better understand how microscale pedestrian design features (sidewalks, crosswalks, signalization, dedicated bikeways, etc.) can help realize the positive health benefits that walkability can create while minimizing pedestrian/bicyclist mortality risk.

Findings are particularly compelling and timely considering the federal transportation related infrastructure investments being proposed to enhance underserved communities and promote health. Empirical evidence presented highlights the opportunity that by recognizing the relationship between built environment and pedestrian/bicyclist safety, existing walkability assessment techniques (indices) used in the literature can be meaningfully improved to predict and simulate how different investments impact pedestrian/bicyclist safety more accurately. This in turn can provide an evidence-base for transportation engineers, public health officials, urban planners, and policy makers to simultaneously improve health outcomes and minimize safety risks to vulnerable road users.

6. ACKNOWLEDGEMENTS

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7. AUTHOR STATEMENT

BW conceived and designed the study, performed geocoding and creation of neighborhood-level measures, conducted data integration, performed all analyses, interpreted the results, and wrote the original/revised manuscript drafts. LDF helped develop the study design, provided useful feedback, and majorly contributed to the manuscript. All authors have access to the data, gave final approval of this manuscript version, take full responsibility for the content, and are accountable for all aspects of the work.

8. SUPPLEMENTARY INFORMATION

Supporting supplementary information (SI) is provided in Appendix A below (Supplementary Information_bw_v2.docx). The SI includes description of built environment measures, geocoded data distributions, Pearson correlations, description of the methodological framework for modeling fatality rate outcomes, estimation results for all-mode traffic fatality rates, and results of sensitivity analyses.

9. DATA AVAILABILITY

The authors welcome correspondence from anyone interested in learning more about the datasets used in this study. Fatality outcome data are extracted from the publicly available Fatality Analysis Reporting System (FARS) by National Highway Traffic Safety Administration. The environmental data are extracted from the publicly available U.S. EPA’s Smart Location Database. After publication of this study, study protocols, data dictionary, and census-tract level integrated fatality and environmental data may be made available after signing a data sharing and use agreement.

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11. APPENDIX A

Redefining Walkability to Capture Safety: Investing in Pedestrian, Bike, and Street Level Design Features to Make it Safe to Walk and Bike

Supplementary Materials

Table of Contents

Description of Built Environment Measures and Walkability Index (Construction and Interpretation) 2
Supplementary Table 1. Pearson Correlations 5
Neighborhood Fatality Rate Models 6
Overview 6
Tobit Modeling Framework 6
Hierarchical Structure of the Data 6
Hierarchical Three-Level Tobit Modeling Framework 7
Supplementary Table 2. Multilevel Tobit Models for Total Fatality Rate Outcome 8
Supplementary Table 3. Sensitivity Analyses for Pedestrian/Bicyclist Fatality Rate Outcome 9

Supplementary Figure 1. Censored and Uncensored Distributions of Pedestrian/Bicyclist Fatality Rates. 3
Supplementary Figure 2. Censored and Uncensored Distributions of Total Fatality Rates. 4

Description of Built Environment Measures and Walkability Index (Construction and Interpretation)

Neighborhood (census tract) level built environment data were derived from the most recent (version 3.0 – 2021) Smart Location Database (SLD) supported by the U.S. Environmental Protection Agency (EPA) and U.S. General Services Administration (GSA) [1]. The 2021 SLD extends the earlier version 2.0 with methodological enhancements in built environment assessment/evaluation and provides greater coverage nationwide. To explore the links between pedestrian/bicyclist (total) fatalities and urban design, we harnessed fine-grained built environment data related to the "5D" variables – density, urban design, diversity, destination accessibility, and distance to transit - widely used in the literature as key predictors of travel behavior and health outcomes [2, 3]. Specific built environment measures representing the "5D" environmental construct are:

Street Connectivity: Street connectivity represents the urban design texture and quantifies the extent to which destinations can be accessed by pedestrians/bicyclists. By providing direct connectivity to vulnerable road users accessing different destinations, street connectivity supports sustainable travel modes [4-6] and is correlated with lower mortality and morbidity from chronic and infectious diseases [7, 8]. We used intersection density (count of intersections per acre) as a measure of street connectivity. A weighted sum of different intersection density metrics (including multi-modal and pedestrian-oriented three and four leg intersections) was used with auto-oriented intersections assigned a zero weight [1]. A reduced relative weight was used for three-way intersections as they do not promote street connectivity as well as four-leg intersections.

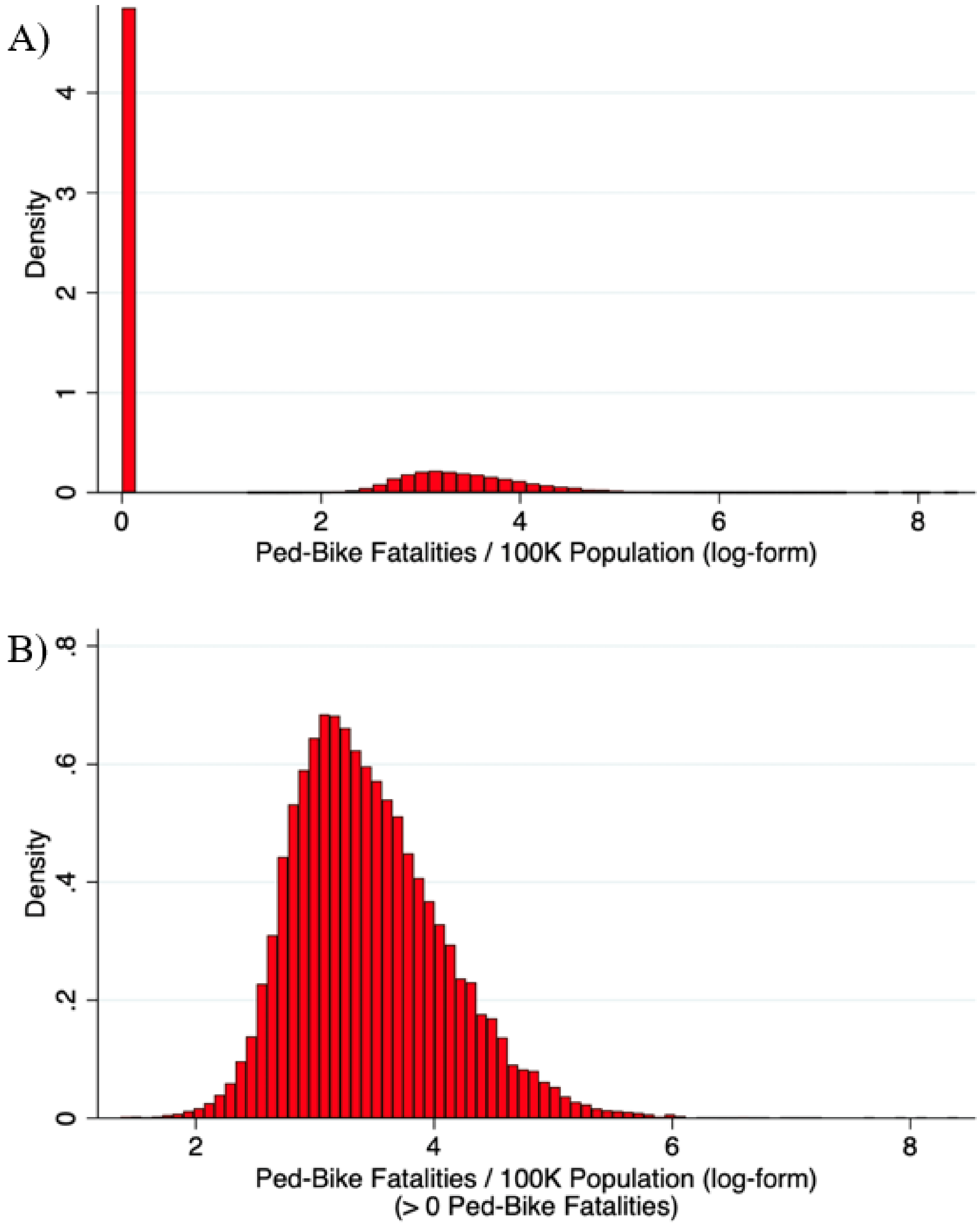
Diversity of Land Uses: While connectivity captures the extent to which destinations can be directly accessed, land-use diversity indicates to what extent different destination types are available for non-motorized users to access. By providing different destination types within a neighborhood, more diverse or mixed land-use discourages sedentary travel. To capture land-use diversity, we considered two key entropy measures that are associated with lower sedentary travel [2, 9], greater active transportation [9, 10], and lower risk of chronic and infectious diseases [11, 12]. The two measures include static eight-tier employment entropy (ranging from 0 to 1) capturing the distribution of different employment types within a neighborhood. Likewise, ranging between 0 and 1, the five-tier employment and residential entropy captures the evenness of residential areas and employment types within a neighborhood. Greater values indicate more diverse land uses supporting a "live, work, and play" lifestyle correlated with sustainable travel behavior [8].

Transit Accessibility: Access to transit is a key predictor of active travel behaviors and health outcomes [13, 14]. Transit accessibility was measured as the minimum walking distance (in meters) between the population-weighted centroid of a neighborhood and the nearest transit stop (of any type).This measure is based on the transit stop data in the U.S. General Transit Feed Specification (GTFS) and incorporates pedestrian network and travel times parsed through an Application Programming Interface [1].

National Walkability Index: The four built environment measures were combined into a composite national walkability index to circumvent the multicollinearity issue that arises with the use of individual built environment features [15]. The walkability index in the U.S. EPA's 2021 SLD version is intended to meet the demand for evidence-based tools enabling end-users to compare places nationwide in a consistent manner for their potential to support active transportation [1]. As an input measure, it also enables transportation scenario-planning efforts aimed at monetizing the health benefits of contrasting urban design and transportation investments. To create the neighborhood walkability index, ranked scores were computed for each of the four component measures above by categorizing neighborhoods into four quartiles. Ranked scores were then estimated for each neighborhood from 1 to 20 (with 20 reflecting highest support for walking) and combined in a weighted elasticity formula as follows [1]:

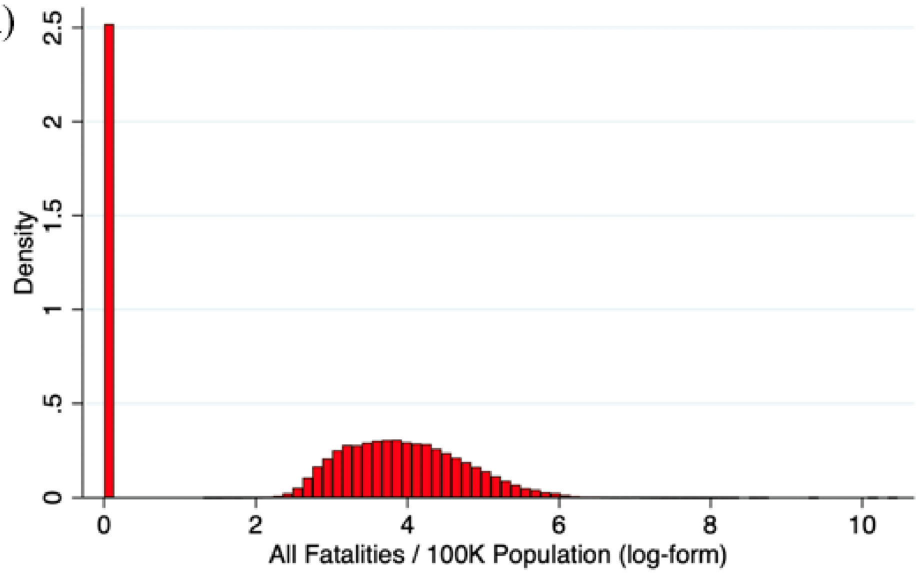
$$National\ Walkability\ Index = \left(\frac{A}{6}\right) + \left(\frac{B}{6}\right) + \left(\frac{C}{3}\right) + \left(\frac{D}{3}\right)$$

Where: A, B, C, and D indicate the neighborhood ranked scores for employment entropy, employment and residential entropy, intersection density, and access to transit. The resulting walkability index ranges from 1 to 20. As a broad reference, the walkability index can be categorized into the following levels: (1) least walkable (0 - 5·75], (2) below average walkable (5·75 - 10·5], (3) above average walkable (10·5 – 15·25], and (4) most walkable (15·25 – 20·0] [1].

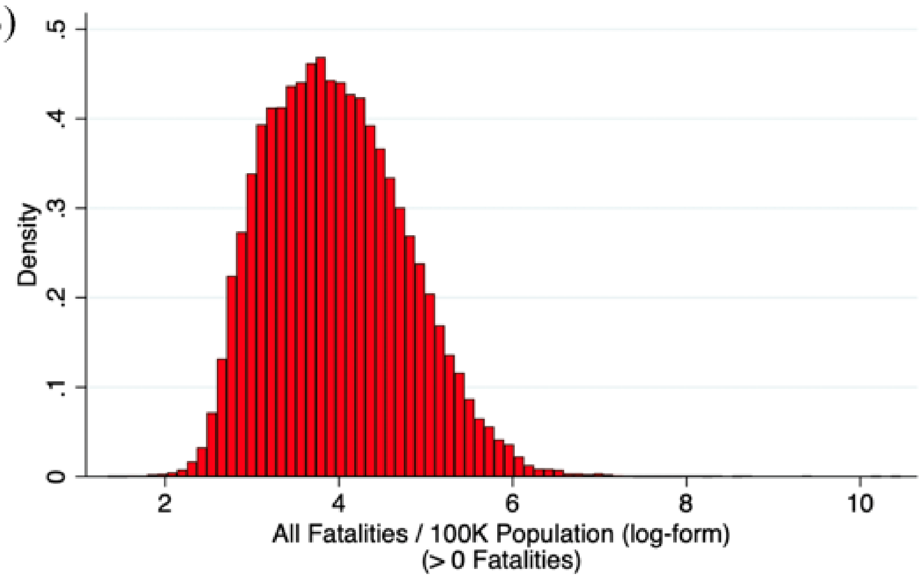


Supplementary Figure 1. Censored and Uncensored Distributions of Pedestrian/Bicyclist Fatality Rates.
Notes: A shows the distribution of log of pedestrian/bicyclist fatalities per 100,000 population. Around 67% of metropolitan neighborhoods (40,086 out of 59,040) had zero pedestrian/bicyclist fatality rates; B shows the distribution of log of pedestrian/bicyclist fatalities per 100,000 population for census tracts with > 0 pedestrian/bicyclist fatality rates. To handle zero fatality rates in the log transformation, we added a value of one to all observations and subsequently calculated the logarithm as log $(\text{pedestrian/bicyclist fatality rate} + 1)$.

A)



B)



Supplementary Figure 2. Censored and Uncensored Distributions of Total Fatality Rates.
Notes: A shows the distribution of log of total fatalities per 100,000 population. Around 33% of metropolitan neighborhoods (19,450 out of 59,040) had zero total (all-mode) fatality rates; B shows the distribution of log of total fatalities per 100,000 population for census tracts with > 0 fatality rates. To handle zero fatality rates in the log transformation, we added a value of one to all observations and subsequently calculated the logarithm as $\log(\text{total fatality rate} + 1)$.

Supplementary Table 1. Pearson Correlations

Variables	Pedestrian/bicyclist fatality rate	Pedestrian/bicyclist fatality rate (log-form)	All fatality rate	All fatality rate (log-form)	National Walkability Index
Pedestrian/bicyclist fatality rate	1				
Pedestrian/bicyclist fatality rate (log-form)	0·572 (0·000)*	1			
All fatality rate	0·6317 (0·000)*	0·1747 (0·000)*	1		
All fatality rate (log-form)	0·3160 (0·000)*	0·5087 (0·000)*	0·2748 (0·000)*	1	
National Walkability Index	0·0777 (0·000)*	0·0958 (0·000)*	-0·0801 (0·000)*	-0·2282 (0·000)*	1

Notes: Pedestrian/bicyclist fatality rate is defined as the number of pedestrian/bicyclist fatalities per 100,000 population; All fatality rate is defined as the number of total fatalities per 100,000 population; Walkability index is a composite measure comprised of average intersection density, five-tier employment and household entropy, 8-tier employment entropy, and distance to nearest transit stop; p-values are shown in parenthesis; * indicate statistical significance with p-value < 0·05.

Neighborhood Fatality Rate Models

Overview

The fatality rate models aim to examine the determinants of neighborhood-level pedestrian/bicyclist and total (all-mode) traffic fatalities per 100,000 population (or developed area). Since the distributions of fatality rates exhibit large spikes at zero (Supplementary Figures 2 and 3), traditional linear regression framework will likely yield inconsistent and biased estimates [16, 17]. Also, the data used in this study are hierarchical in nature leading to correlations among neighborhood-level safety outcomes. The next sections briefly present the statistical framework to deal with this issue and presents a multi-level modeling framework to accommodate the hierarchical structure of the data.

Tobit Modeling Framework

The large-spikes at zero in the distributions of fatality rate outcomes represent a "corner-solution'. Unlike censoring, the corner-solution does not represent a data observability issue. Instead, an outcome of zero fatality rate is true outcome indicating a safer neighborhood state and follows a positive probability. To adequately handle the corner-solution, Tobit modeling framework can be implemented with the following generalized structural form:

$$Y_i^* = \beta X_i + \varepsilon_i; \quad (i = 1, 2, \dots, N) \tag{1}$$

Where: Y_i^* is a latent variable parametrized as a function of observed exogenous variables (X_i) and is observed for logarithm of fatality rates greater than τ and censored otherwise; β is a vector of estimable parameters associated with X_i; ε_i indicates the unobserved error terms following a normal density; N is an index for neighborhoods. The latent log fatality rates can be mapped to observed counterparts (indicated by Y) using the following mapping (measurement) system [16, 17]:

$$\begin{aligned} Y_i &= Y_i^* \; if \; Y_i^* > \tau \\ Y_i &= \tau_Z \; if \; Y_i^* \leq \tau \end{aligned} \tag{2}$$

And, with the following likelihood function [18]:

$$L = \prod_{i}^{N} \left[\frac{1}{\sigma} \phi \left(\frac{Y_i - \beta X_i}{\sigma} \right) \right]^{d_i} \left[1 - \Phi \left(\frac{\beta X_i}{\sigma} \right) \right]^{1-d_i} \tag{3}$$

Where: Φ and ϕ indicate a standard cumulative normal distribution and standard normal density functions, respectively; τ is the lower limit (corner-solution) of log fatality rate distributions (in this case zero). The final log-likelihood function is formulated below – with the first part being a traditional regression for uncensored (non-zero) observations and the second part representing the estimable probabilities that a specific observation is at the corner-solution (lower limit) [18]:

$$lnL = \sum_{i=1}^{N} \left\{ d_i \left(-ln\sigma + ln\phi \left(\frac{Y_i - \beta X_i}{\sigma} \right) \right) + (1 - d_i) ln \left(1 - \Phi \left(\frac{\beta X_i}{\sigma} \right) \right) \right\} \tag{4}$$

Hierarchical Structure of the Data

The data used in this study exhibit an inherent nested hierarchical structure with individual neighborhoods (census tracts) nested within states which are in turn nested within regions. Given this hierarchical structure, it is very likely that traffic fatality rates of neighborhoods within the same state are correlated due to the presence of common observed and unobserved state-level factors. Likewise, neighborhood safety outcomes within a region could be correlated due to observed and unobserved regional factors. The multi-level hierarchical extension of the Tobit models below used the following nested structure:

- All 51 U.S. states, and;

- Nine U.S. Regions including North East: New England, North East: Mid Atlantic, Mid West: East North, Mid West: West North, South: South Atlantic, South: East South, South: West South, West: Mountain, West: Pacific.

Hierarchical Three-Level Tobit Modeling Framework

To account for the hierarchical structure of the data, a variance-component model is used within the overarching structural component of the Tobit model in Eq. (1) leading to multi-level random intercepts as:

Neighborhood-level: $$Y^*_{kji} = \beta_{kj0} + e_{kji} \tag{5}$$

State-level: $$\beta_{kj0} = \aleph_{k00} + \beth_{kj0} \tag{6}$$

Region-level: $$\aleph_{k00} = \kappa_{000} + \Theta_{k00} \tag{7}$$

The hierarchical random effects can be combined into a single index function as:

$$Y^*_{kji} = \kappa_{000} + \Theta_{k00} + \beth_{kj0} + e_{kji} \tag{8}$$

Where:

Y^*_{kji} = pedestrian/bicyclist (total) log fatality rate for i^{th} neighborhood in j^{th} state and k^{th} region with $i = 1,2,\dots,R_{kj}$, $j = 1,2,\dots,R_k$, and $k = 1,2,\dots,R$;
κ_{000} is the grand mean fatality rate for all neighborhoods;
Θ_{k00} is the random effect at regional-level;
$\beth_{kj0}$ is the random effect at state-level;
e_{kji} is the random effect at neighborhood-level.

The hierarchical random effects $[\Theta_{k00},\ \beth_{kj0},\ e_{kji}]$ are specified as normally distributed as: $\Theta_{k00} \sim N(0, \delta^2_{\Theta})$, $\beth_{kj0} \sim N(0, \delta^2_{\beth})$, and $e_{kji} \sim N(0, \delta^2_e)$ – with the hierarchical random effect variances approximating the total variance in pedestrian/bicyclist (total) log fatality rates among neighborhoods, states, and regions. The resulting framework accommodates the hierarchical nesting of neighborhoods and accounts for the underlying dependencies in the neighborhood-level safety outcomes.

Supplementary Table 2. Multilevel Tobit Models for Total Fatality Rate Outcome

Variable	Model 3				Model 4			
	β	95% CI	Marginal Effect	95% CI	β	95% CI	Marginal Effect	95% CI
Built Environment								
Walkability Index (WI)	-0·010	[-0·018, -0·001]	-0·008	[-0·014, -0·001]	··	··	··	··
WI: Quartile 1 (base)	··	··	··	··	··	··	··	··
WI: Quartile 2	··	··	··	··	-0·614	[-0·685, -0·543]	-0·485	[-0·543, -0·427]
WI: Quartile 3	··	··	··	··	-0·652	[-0·731, -0·573]	-0·514	[-0·578, -0·45]
WI: Quartile 4	··	··	··	··	-0·366	[-0·455, -0·277]	-0·294	[-0·366, -0·222]
Behavioral Exposure (% of commuters)								
Drive alone	0·005	[0·003, 0·007]	0·004	[0·002, 0·005]	0·008	[0·006, 0·011]	0·007	[0·005, 0·008]
Teleworking	0·006	[-0·001, 0·013]	0·005	[-0·001, 0·010]	0·007	[0, 0·013]	0·005	[0, 0·01]
Average household daily vehicle miles traveled (VMT)	0·079	[0·075, 0·082]	0·061	[0·058, 0·064]	0·071	[0·068, 0·074]	0·055	[0·052, 0·058]
VMT missing dummy	2·479	[2·273, 2·686]	1·919	[1·754, 2·084]	2·277	[2·072, 2·482]	1·762	[1·599, 1·925]
Sociodemographic Factors (% of population)								
Female	-0·032	[-0·037, -0·026]	-0·025	[-0·029, -0·020]	-0·028	[-0·033, -0·022]	-0·021	[-0·026, -0·017]
Black	0·007	[0·006, 0·008]	0·006	[0·005, 0·007]	0·008	[0·007, 0·009]	0·006	[0·005, 0·007]
Graduate	-0·027	[-0·03, -0·024]	-0·021	[-0·023, -0·018]	-0·024	[-0·027, -0·021]	-0·019	[-0·021, -0·016]
Low income	0·042	[0·04, 0·044]	0·033	[0·031, 0·034]	0·04	[0·038, 0·042]	0·031	[0·029, 0·033]
Age: 18-29 years	-0·014	[-0·016, -0·011]	-0·011	[-0·013, -0·008]	-0·012	[-0·015, -0·009]	-0·009	[-0·012, -0·007]
Constant	-0·510	[-0·94, -0·079]	··	··	-0·364	[-0·775, 0·046]	··	··
Heterogeneity								
Variance: Regional level (constant)	0·035	[0·008, 0·154]	··	··	0.033	[0.007, 0.149]	··	··
Variance: State level (constant)	0·112	[0·069, 0·181]	··	··	0.111	[0.068, 0.178]	··	··
Variance: Residuals	6·501	[6·401, 6·601]	··	··	6.434	[6.336, 6.534]	··	··

Notes: Response outcome is log (total fatality rate + 1); total fatality rate equals # of total (all-mode) fatalities per 100,000 population; (··) is Not Applicable; CI is confidence interval; ME is average marginal effect; Models 3 and 4 include continuous walkability index and quartiles of walkability index, respectively; The four walkability index (WI) quartiles correspond to: (min, WI25P], (WI25P, WI50P], (WI50P, WI75P], (WI75P, max] – where "P" indicates the corresponding percentiles of walkability index; N = 59,038 census tracts; Uncensored N = 39,589; Left-censored N = 19,449; Log-likelihood at convergence and Akaike Information Criterion equal -111,384·50 and 222,796·90 (for Model 3) and -111,182·02 and 222,396 (for Model 4), respectively; Hierarchical grouping information for Model 3 and 4: Number of regions = 9; N per region [minimum, average, maximum] = [2,821, 6,559·8, 11,709]; Number of states = 51; N per state [minimum, average, maximum] = [39, 1,157·6, 7,474]; Both multi-level Tobit models include hierarchical region and state-specific random effects; All statistics shown have p-values < 0·005 except Walkability Index (WI) (0·02), Teleworking (0·09), Constant (0·02) (in Model 3) and Teleworking (0·057) and Constant (0·082) (in Model 4). The average marginal effects (MEs) are obtained from multilevel Tobit utility functions pertaining to the actual response outcome including both censored and uncensored observations, i.e., true corner-solution setting. Since the dependent variables are log-transformed, multiplying the MEs by 100 indicates the % change in total fatality rates with a unit increase in continuous variable or a switch from 0 to 1 (for binary variables).

Supplementary Table 3. Sensitivity Analyses for Pedestrian/Bicyclist Fatality Rate Outcome

Category	Models	ME	p-value	95% CI	
Normalization by Developed Area	**Model 1A: Natural log of ped-fatalities / 100 miles of developed area**				
	Walkability index	0.087	0·000	0.076	0.099
	[N, $LL_{CONVERGENCE}$]		[59,038, -77863·7]		
Regional Models (Natural logarithm of pedestrian/bicyclist fatalities / 100,000 population)	**Model 1B: Region 1 (North East: New England)**				
	Walkability index	0·053	0·000	0·025	0·081
	[N, $LL_{CONVERGENCE}$]		[2,821, 2818·04]		
	Model 1C: Region 2 (North East: Mid Atlantic)				
	Walkability index	0·058	0·000	0·041	0·075
	[N, $LL_{CONVERGENCE}$]		[9,049, -9801·87]		
	Model 1D: Region 3 (Mid West: East North)				
	Walkability index	0·038	0·000	0·023	0·052
	[N, $LL_{CONVERGENCE}$]		[9,326, -9637·32]		
	Model 1E: Region 4 (Mid West: West North)				
	Walkability index	0·019	0·072	-0·001	0·041
	[N, $LL_{CONVERGENCE}$]		[3,224, -3096·99]		
	Model 1F: Region 5 (South: South Atlantic)				
	Walkability index	0·063	0·000	0·048	0·078
	[N, $LL_{CONVERGENCE}$]		[11,709, -16624·43]		
	Model 1G: Region 6 (South: East South)				
	Walkability index	0·088	0·000	0·061	0·117
	[N, $LL_{CONVERGENCE}$]		[2,838, -3690·23]		
	Model 1H: Region 7 (South: West South)				
	Walkability index	0·049	0·000	0·031	0·067
	[N, $LL_{CONVERGENCE}$]		[6,360, -9044·88]		
	Model 1I: Region 8 (West: Mountain)				
	Walkability index	0·065	0·000	0·044	0·086
	[N, $LL_{CONVERGENCE}$]		[4,083, -5296·11]		
	Model 1J: Region 9 (West: Pacific)				
	Walkability index	0·038	0·000	0·024	0·052
	[N, $LL_{CONVERGENCE}$]		[9,628, -13267·5]		
Neighborhoods with pedestrian/bicyclist fatalities	**Model 1K: Natural log of pedestrian/bicyclist fatalities / 100,000 population (census tracts with > 0 pedestrian/bicyclist fatalities)**				
	Walkability index	0·018	0·000	0·015	0·022
	[N, $LL_{CONVERGENCE}$]		[18,953, -16853·04]		

Notes: ME is average marginal effect; N is sample size (# of metropolitan neighborhoods); CI is confidence interval; $LL_{CONVERGENCE}$ is log-likelihood at convergence; Dependent variable is logarithm of pedestrian/bicyclist fatalities per 100,000 population except Model 1A (logarithm of pedestrian/bicyclist fatalities per 100 miles of developed area) and Model 1K (logarithm of pedestrian/bicyclist fatalities per 100,000 population for census tracts with > 0 pedestrian/bicyclist fatalities); Where applicable, logarithms were computed as log ($fatality\ rate + 1$) to handle neighborhoods with zero pedestrian/bicyclist fatalities rates (see methods); Model 1A is a multi-level hierarchical Tobit model with nested random effects for U.S. states and regions. Models 1B through 1J are regional multi-level Tobit models with random effects for U.S. states (except for Model 1G where a multi-level Tobit model failed to converge and is thus based on a fixed parameter non-hierarchical Tobit specification). Model 1K is based on a multi-level hierarchical linear regression model (instead of a Tobit framework since neighborhoods with 0 pedestrian/bicyclist fatalities were discarded) with nested random effects for U.S. states and regions. Since the dependent variables are log-transformed, multiplying the MEs by 100 indicates the % change in pedestrian/bicyclist fatality rates with a unit increase in continuous variable or a switch from 0 to 1 (for binary variables). All models controlled for behavioral exposure and sociodemographic factors, namely, % Low Income, % Black, % Graduate, % Female, vehicle miles travelled, Teleworking, and polynomial terms for Active Travel and Age: 18-29 years.

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