The Effects of Roadway and Built Environment Characteristics on Pedestrian Fatality Risk: a National Assessment at the Neighborhood Scale

Theodore J Mansfield[a,*], Dana Peck[b], Daniel Morgan[c], Barbara McCann[d], Paul Teicher[e]

[a] Data Fellow, Oak Ridge Institute for Science and Education, US Department of Transportation, Office of Policy Development, Strategic Planning and Performance, 1200 New Jersey Avenue, Washington, DC 20590. theodore.mansfield@rsginc.com

[b] Data Fellow, Oak Ridge Institute for Science and Education, US Department of Transportation, Office of Policy Development, Strategic Planning and Performance, 1200 New Jersey Avenue, Washington, DC 20590. dpeck88@gmail.com

[c] Chief Data Officer, US Department of Transportation, Office of the Chief Information Officer 1200 New Jersey Avenue, Washington, DC 20590. daniel.morgan@dot.gov

[d] Director, US Department of Transportation, Office of Policy Development, Strategic Planning and Performance, 1200 New Jersey Avenue, Washington, DC 20590. barbara.mccann@dot.gov

[e] Senior Policy Analyst, US Department of Transportation, Office of Policy Development, Strategic Planning and Performance, 1200 New Jersey Avenue, Washington, DC 20590. paul.teicher@dot.gov

[*] Corresponding author

Keywords: pedestrian safety; risk assessment; crash risk; built environment; traffic safety; public health

Conflicts of interest: None to declare.

ABSTRACT

Characteristics of the transportation system and built environment contribute to pedestrian fatality risks, including vehicular traffic and land-use characteristics associated with higher pedestrian activity. We combined data from FHWA, NHTSA, EPA, and the Census Bureau and performed regression modeling to explore associations between transportation system and built environment characteristics and pedestrian fatalities between 2012 and 2016 at the Census tract scale across the United States. In urban tracts, we found especially strong associations between traffic on non-access-controlled principal arterial and minor arterial roadways and pedestrian fatalities (0.91 and 0.68 additional annual pedestrian fatalities per 100,000 persons per 10,000 VMT/mi^2 increase in traffic density, respectively). In both urban and rural tracts, we also found strong associations between employment density in the retail sector and pedestrian fatalities. Finally, we compared our model to the High Injury Network in Los Angeles, CA. Nearly half (43%) of observed fatalities were identified by both methods, while some fatalities were identified by only one (19% by our model and 23% by the High Injury Network). This work shows that traffic on certain roadway facility types and employment in certain sectors have especially strong associations with pedestrian fatality risk. More broadly, we illustrate how leveraging cross-disciplinary data in novel ways can support prospective, risk-based assessments of pedestrian fatality risks and support integrated and systemic approaches to transportation safety.

1. INTRODUCTION

Over the last several decades, traffic fatalities in the United States (US) decreased substantially. However, reductions in traffic fatalities have not been shared equally across transportation modes. Between 2006 and 2014, yearly motor vehicle occupant fatalities decreased by 27% while yearly pedestrian fatalities increased by 3%. Recently, traffic fatalities have risen sharply—from 32,744 in 2014 to 37,461 in 2016—and pedestrian fatalities have accounted for 23% of this increase. (National Center for Statistics and Analysis, 2017a). Pedestrian fatalities now account for 16% of all traffic fatalities in the US, the highest percentage on record (National Center for Statistics and Analysis, 2017b).

A range of policies, including infrastructure-based safety improvements, seat belt laws, and vehicle safety design standards, have prompted historic reductions in motor vehicle occupant deaths (Bunn et al. 2003; Cohen and Einav, 2003). Today, states and metropolitan planning organizations (MPOs) are preparing to set non-motorized safety performance targets as required under the Moving Ahead for Progress in the 21st Century Act (2012). Further, state and local transportation agencies in the US are increasingly integrating pedestrian safety into routine practice (Lyons et al. 2014; Singleton and Clifton, 2017). However, transportation agencies often retroactively designate high-risk areas to prioritize countermeasures—for example, identifying high-risk corridors based on past fatalities (Johansson, 2009). Because pedestrian fatalities are relatively rare events influenced by many factors, retrospective approaches may not sufficiently characterize pedestrian fatality risk. Further, changes in the built environment and transportation system may modify pedestrian fatality risk in ways that could not be anticipated by a retrospective approach. Thus, characterizing associations between pedestrian fatality risk and transportation system, built environment, and sociodemographic characteristics may help transportation agencies adopt more forward-thinking approaches to reducing pedestrian fatalities.

Previous studies have sought to characterize pedestrian fatality risk factors at a variety of spatial scales. At the facility scale, specific roadway design elements, such as the presence of sidewalks and crosswalks, have been shown to reduce pedestrian risks (Conway et al. 2013; Das and Sun, 2015; Sarwar et al. 2017). Neighborhood-scale factors, including traffic density, sociodemographic factors, population density, and land use have demonstrated associations with pedestrian risks (Abdel-Aty et al., 2013; Amoh-Gyimah et al. 2016; Cottrill and Thakuriah, 2010; Ukkusuri et al. 2011). Finally, regional characteristics, such as percent of the population walking to work, have also been associated with pedestrian fatalities (Behnood and Mannering 2016; Jacobsen, 2003). However, the scalability and generalizability of previous studies are often limited. Facility-level studies may use modeled or observed pedestrian and vehicle volumes for specific facilities—data that are unavailable at larger scales. Neighborhood-scale studies often use measures of exposure that are more widely available but less precise, such as population walking to work, and may lack detailed transportation system and/or built environment characteristics. Regional-scale studies do not consider small-scale built environment variations that shape pedestrian behavior, producing findings that are meaningful in the aggregate but have limited usefulness to practitioners seeking to reduce risk in specific contexts. Finally, it can be difficult to discern the individual of effects of transportation, built environment, and sociodemographic factors on pedestrian fatality risk because lower-income neighborhoods often have lower-quality pedestrian environments (Singh et al., 2010). While previous work identified many factors associated with pedestrian fatalities, the limited scalability and generalizability of previous studies restrict their applicability in real-world decision-making contexts.

To address the need for a generalizable pedestrian fatality risk model, we combined elements of facility-level studies (fine-scaled transportation system data) and area-wide studies (built environment data) with geo-coded pedestrian fatality records from the Fatality Analysis Reporting System (FARS) to characterize Census tract scale pedestrian fatality risk across the US. We then applied our model to in Los Angeles, CA and compared our estimates to the city's High Injury Network (HIN). To our knowledge, this is the first study to combine high-resolution traffic, employment, and built environment data with sociodemographic information to characterize neighborhood-level pedestrian fatality risks at the national scale in the US. This work could inform the development of risk-based decision-support tools to help proactively identify high-risk neighborhoods for pedestrians and support estimates of how changes in the built environment and transportation system could shape pedestrian fatality risk.

2. MATERIALS AND METHODS

2.1 Urban/Rural Tract Designation

Because different factors may affect pedestrian fatality risk in urban and rural contexts, we stratified tracts into urban (n=50,027) and rural (n=22,711) categories. An urban tract was defined as having >50% of its area within Census urbanized areas or having a population density greater than 1,000 persons/mi^2 (Census Bureau Urban Area Criteria for the 2010 Census, 2011).

2.2 Data Sources

We obtained geo-coded pedestrian fatality records, transportation system and built environment characteristics, and sociodemographic data for all Census tracts in the US (Table 1).

2.2.1 Pedestrian Fatalities

The FARS database contains records of all traffic fatalities that occur in the US (National Highway Traffic Safety Administration, 2016). We extracted geo-coded pedestrian fatalities that occurred between 2012 and 2016 from FARS (n=25,615; n=374 records not included due to missing geo-coordinates) and assigned records to the Census tract in which they occurred.

2.2.2 Transportation System

The Federal Highway Administration (FHWA) Highway Performance Monitoring System (HPMS) contains roadway characteristic information for all public roadways in the US and is updated yearly (Federal Highway Administration, 2016a). Roadway segments in the HPMS are broken into seven functional classifications (FC) based on function and design characteristics: FC1) interstates, FC2) other freeways and expressways, FC3) other principal arterials, FC4) minor arterials, FC5) major collectors, FC6) minor collectors, and FC7) local roads. FC1 and FC2 roadways have full access control while FC3 through FC7 roadways have partial or no access control (Federal Highway Administration, 2013). States are required to report annual average daily traffic (AADT) to FHWA using uniform methods for all FC1–5 and urban FC6 roadways; however, states may report AADT on rural FC6, rural FC7, and urban FC7 roadways using their own methods (Federal Highway Administration, 2016b). Due to potential variation in AADT reporting between states, rural FC6, rural FC7, and urban FC7 roadways were excluded.

We used HPMS AADT data to calculate average traffic density for all Census tracts in the US by functional classification for each year between 2012 and 2016. To do so, we first multiplied AADT by segment length to estimate average daily vehicle-miles travelled (VMT) for all HPMS segments. Next, we assigned VMT to the Census tract(s) in which road segments are located. Roadways often form the boundaries of tracts, presenting two difficulties in accurately assigning VMT to tracts. First, HPMS line segments that form tract boundaries may be located entirely within one tract or zigzag between adjacent tracts, potentially resulting in arbitrary assignment of VMT to tracts. Second, traffic on a roadway that forms the boundary between two tracts likely contributes to pedestrian fatality risk in both adjacent tracts. To more accurately assign VMT to tracts, we first generated 50 foot buffers around each HPMS segment and calculated VMT density *(VMT/mi^2)* within each buffer b for each roadway functional class, $VMT_{b,FC}$. We then calculated the intersecting area between each buffer b and each tract t, $A_{b,t}$ and assigned the value of $VMT_{b,FC}$ to each area $A_{b,t}$ within buffer b. Tract-level VMT density by functional classification was then calculated by $VMT_{b,FC}$ for n $A_{b,t}$ within each tract:

$$VMT_{t,FC} = \frac{\sum_{i=1}^{n} A_{b,t} \times VMT_{b,FC}}{A_t} \qquad (1)$$

Where $VMT_{t,FC}$ is VMT density in tract t for functional classification FC and A_t is the land area of tract t. Finally, we combined FC1 and FC2 into a single category (interstates, freeways, and expressways) because these functional classifications share full access control.

2.2.3 Population Walking Behaviors

Data measuring walking at the national scale are sparse. Reported walking to work is available in the American Community Survey (ACS) (Census Bureau, 2016a). However, walking prevalence is under-reported in the ACS relative to other surveys that also measure non-commute walking (Whitfield et al., 2015). Individuals who commute to work via public transit also walk more than the general population (Freeland et al., 2013; Mansfield and MacDonald Gibson, 2016). To capture walking prevalence, walking and public transit commuting were obtained from the ACS for each year between 2012 and 2016. Additionally, we obtained built environment measures with demonstrated associations with walking as proxies for non-commute walking: population and employment density, land-use diversity, and physical design (Ewing and Cervero, 2010).

2.2.4 Population and Employment Density

We estimated daily average tract population by averaging ACS-reported (household-based) and estimated daytime (work-based) populations as recommended by the Census Bureau (no date):

$$Pop_t = \frac{ResPop_t + (ResPop_t + FlowIn_t - FlowOut_t)}{2} \quad (2)$$

where Pop_t is the average daily population in tract t, $ResPop_t$ is the residential (ACS reported) population in tract t, $FlowIn_t$ is the sum of commuter flows in to tract t, and $FlowOut_t$ is the sum of commuter flows out of tract t.Tract-to-tract commuter flows were obtained by aggregating block-to-block origin-destination commuting data reported in the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) data (Census Bureau, 2016b).

Tract-level employment density was obtained by aggregating LODES worker area comparison data into five employment categories: office (NAICS sectors 51-55 and 92); retail (sectors 44-45); industrial, transportation, and warehousing (sectors 11, 21-23, 31-33, 42, and 48-49); general services (sectors 54, 56, 61-62, and 81); and entertainment, accommodation, and food services (sectors 71-72). LODES data were obtained for each year between 2012 and 2015, the most recent year for which data are available. 2015 values were used in place of 2016 values.

2.2.5 Land-Use Diversity

Land-use diversity measures are typically calculated using local land-use data, such as parcel databases. Because detailed land-use data are not uniformly available across the US, we calculated a measure of activity diversity within each tract using employment in the categories described previously and residential population data (Cervero and Kockelman, 1997):

$$ADI_t = \frac{-A_t}{ln(N_t)} \quad (3)$$

where A_t =

$$\frac{a_{1,t}}{a_{T,t}} \times ln\left(\frac{a_{1,t}}{a_{T,t}}\right) + \frac{a_{2,t}}{a_{T,t}} \times ln\left(\frac{a_{2,t}}{a_{T,t}}\right) + \frac{a_{3,t}}{a_{T,t}} \times ln\left(\frac{a_{3,t}}{a_{T,t}}\right) + \frac{a_{4,t}}{a_{T,t}} \times ln\left(\frac{a_{4,t}}{a_{T,t}}\right) + \frac{a_{5,t}}{a_{T,t}} \times ln\left(\frac{a_{5,t}}{a_{T,t}}\right) + \frac{a_{6,t}}{a_{T,t}} \times ln\left(\frac{a_{6,t}}{a_{T,t}}\right) \quad (4)$$

where ADI_t is the activity diversity index in tract t, N_t is the number of activities present in tract t, $a_{1,t}$ is the residential population in tract t, $a_{2,t}$ is office employment in tract t, $a_{3,t}$ is retail employment in tract t, $a_{4,t}$ is industrial, transportation, and warehousing employment in tract t, $a_{,t5}$ is general services employment in tract t, a_6, t is entertainment, accommodation, and food services employment in tract t, and $a_{T,t}$ is total activity (sum of residential population and all employment) in tract t. When calculating ADI_t for 2016, 2015 LODES data twice in place of 2016 LODES data. ADI_t was scaled to range from 0 (no variation between activity categories within tract) to 100 (maximum variation).

2.2.6 Physical Design

As a proxy for neighborhood physical design, we used two intersection density measures obtained from EPA’s Smart Location Database: the density of auto-oriented intersections, defined as the intersection of at least two access-controlled facilities, two-way roadways with speed limits greater than 55 miles per hour, one-way roadways with speed limits greater than 40 miles per hour, or arterials with four or more travel lanes in one direction; and the density of multi-modal intersections, defined as the intersection of at least two arterials with speed limits less than 55 miles per hour when travel is permitted in both directions or less than 40 miles per hour when travel is permitted in only one direction, local arterials and streets, or pedestrian pathways/trails (Environmental Protection Agency, 2013).

2.2.7 Sociodemographic Data

Census tract median household income, race/ethnicity, percent of zero-vehicle households, and the age and sex distribution of the population were taken from the ACS (Census Bureau, 2016a). If tract-level data for median household income were missing, county-level data were used.

	Urban tracts (n=50,027)			Rural tracts (n=22,711)		
	Mean	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**
Transportation system variables						
VMT density *(thousand VMT/mi^2)*						
Interstates, freeways, and expressways	32.4	0	91.2	1.88	0	5.78
Non-access-controlled principal arterials	19.4	10.6	30.0	1.26	0.264	2.47
Minor arterials	15.6	10.5	17.8	1.01	0.364	1.95
Major collectors [a]	7.16	3.99	10.5	0.749	0.411	0.974
Built environment variables						
Residential population density *(persons/mi^2)*	7,590	3,870	13,700	188	95.9	221
Average daily population density *(persons/mi^2)*	7,710	3,820	17,600	179	87.6	212
Employment density *(employees/mi^2)*						
Office	660	61.0	7,630	6.90	0.946	30.4
Retail	323	93.5	1,790	7.83	1.16	20.2
Industrial, transportation and warehousing	427	92.5	3,970	20.7	5.09	50.0
General services	1,610	363	11,800	22.1	4.68	50.0
Entertainment & food/accommodation services	401	92.5	2,600	7.12	1.00	21.9
Activity mix index *(unitless)*	41.4	39.4	21.7	37.9	36.3	17.8
Intersection density *(count/mi^2)*						
Auto-oriented intersection	1.73	0.282	3.94	0.210	0.0923	0.333
Non-auto-oriented intersections	13.6	9.58	14.3	1.37	0.693	1.74
Work commute *(%)*						
Walk commute	3.47	1.55	6.36	2.30	1.39	3.65
Transit commute	7.56	2.39	13.4	0.672	0.165	1.83
Sociodemographic variables						
Race/Ethnicity *(%)*						
Non-Hispanic White	55.1	62.5	30.3	80.0	89.3	21.9
Non-Hispanic Black	16.2	5.61	24.0	7.05	1.07	14.1
Hispanic	19.1	9.52	22.7	7.78	2.89	13.8
Non-Hispanic Asian	6.04	2.57	9.79	1.22	0.382	3.32
Non-Hispanic Other	3.08	2.38	3.27	3.42	1.69	8.55
Age and sex distribution *(%)*						
Female, younger than 18	11.1	11.2	3.85	11.1	11.1	2.92
Female, 18-24	5.26	4.37	4.99	3.84	3.54	2.29
Female, 25-34	7.25	6.94	3.23	5.29	5.18	1.85
Female, 35-44	6.50	6.54	1.93	6.00	6.00	1.59
Female, 45-54	6.95	7.03	2.12	7.45	7.47	1.87
Female, 55-64	6.16	6.15	2.18	7.15	7.10	2.04
Female, 65 or older	7.79	7.09	4.72	8.81	8.52	3.48
Male, younger than 18	11.6	11.7	3.96	11.7	11.7	3.03
Male, 18-24	5.36	4.49	4.86	4.40	3.94	3.19
Male, 25-34	7.29	6.80	3.62	5.60	5.27	2.64
Male, 35-44	6.42	6.31	2.22	6.12	5.98	2.02
Male, 45-54	6.67	6.65	2.14	7.47	7.45	1.99
Male, 55-64	5.59	5.54	2.03	7.04	7.01	2.02
Male, 65 or older	5.67	5.14	3.59	7.60	7.29	3.21
Median household income *(thousand USD)*	60.3	54.7	27.3	55.0	51.2	19.1
Census tract land area *(mi^2)*	1.70	0.994	2.11	151	42.0	959
Census tract inhabited land area *(mi^2)*	0.766	0.654	0.529	3.62	3.62	1.24

[a] Includes minor collectors in urban areas

Table 1. Summary Statistics of Explanatory Variables

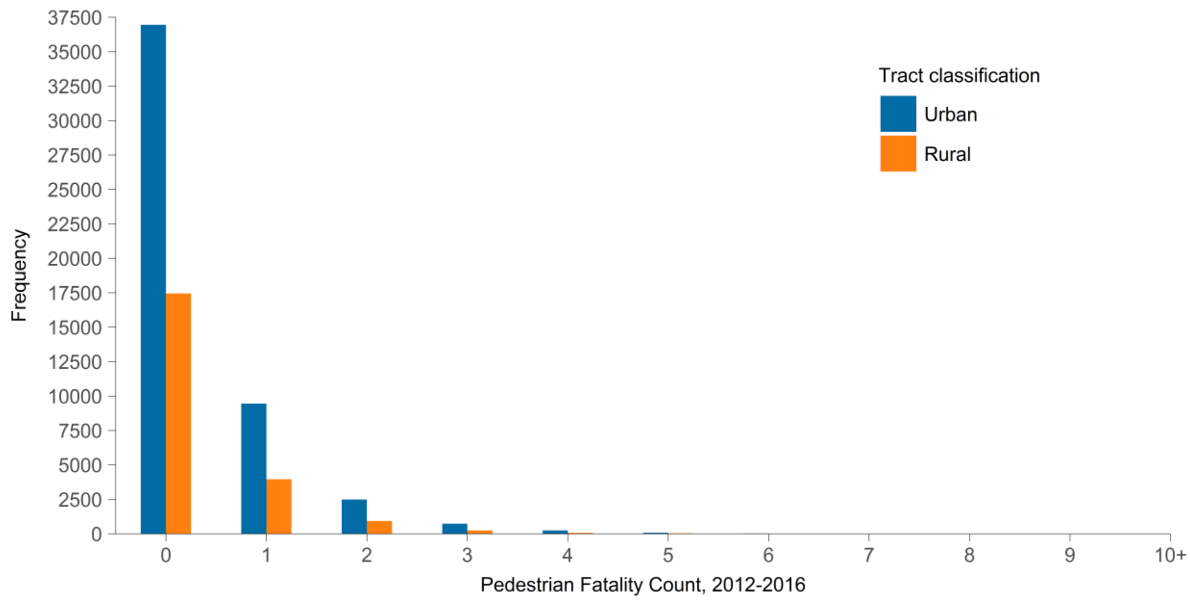

Figure 1. Histogram of pedestrian fatality counts in urban (blue) and rural (orange) tracts

2.3 Regression Models

Because pedestrian fatalities are relatively rare events when assessed at the Census tract geography, all data were pooled over the five-year study period prior to fitting regression models. The resulting distribution of pedestrian fatality counts contain 74% and 77% zero values in urban and rural tracts, respectively (Figure 1). A range of models have been applied in the literature to address excess zeroes in count data, such as zero-inflated models (Mannering and Bhat, 2014). Unobserved heterogeneity, an important potential source of bias in aggregate count models, has been addressed using techniques such as random parameter estimation and spatial autocorrelation modeling (Amoh-Gyimah et al., 2016; Anastasopoulos, 2016).

We first estimated negative binomial (NB) models with random effects at the Census Combined Statistical Area (CSA) level for urban and rural tracts, using average daily tract population, Pop_t, as an offset to convert pedestrian fatality counts to population rates:

$$\lambda_t = exp\big(ln(Pop_t) + \boldsymbol{\beta X_t} + \varepsilon_t + \theta_g\big) \quad (5)$$

where λ_t is the expected number of pedestrian fatalities in tract t, $\boldsymbol{X_t}$ is a vector of explanatory variables, $\boldsymbol{\beta}$ is a vector of model parameters, ε_t is an error term, and θ_g is a random effect for group g. The probability density function for y_i is:

$$P(y_t) = \left(\frac{1/\alpha}{(1/\alpha) + \lambda_t}\right)^{1/\alpha} \frac{\Gamma[(1/\alpha) + \lambda_t]}{\Gamma(1/\alpha)y_t!}\left(\frac{\lambda_t}{(1/\alpha) + \lambda_t}\right)^{y_t} \quad (6)$$

Because previous work has noted that zero-inflated models outperform other model types when zero counts constitute at least 65% of observed counts, we then estimated zero-inflated negative binomial (ZINB) models with CSA-level random effects (Dong et al., 2014). While it is not immediately apparent which variables define the zero state in this study, it is feasible that zero-state tracts predominantly contain roadways with very few pedestrians or roadways with very safe pedestrian environments. We restricted the logit portion of our ZINB models to include only variables related to the most proximate causes of pedestrian fatalities—traffic density, physical design of the built environment, residential/employment density, and observed walk/transit commuting to work. Sociodemographic variables were included only in the conditional portion of the model. This model may be expressed as:

$$P(y_t = j) = \begin{cases} \pi_t + (1 - \pi_t)g(y_t = 0) & if\ j = 0 \\ (1 - \pi_t)g(y_t) & if\ j > 0 \end{cases} \quad (7)$$

where $g(y_t)$ is the negative binomial distribution as defined in (6) and π_t is the logistic link function, given by:

$$\pi_t = \frac{\mu_t}{1 + \mu_t} \quad (8)$$

where:

$$\mu_t = exp\big(ln(Pop_t) + \boldsymbol{YZ_t} + \varepsilon_t + \phi_g\big) \quad (9)$$

where $\boldsymbol{Z_t}$ is a vector of explanatory variables, $\boldsymbol{Y}$ is a vector of model parameters, ε_t is a gamma-distributed error term, and θ_g is a random effect for group g.

Finally, we estimated ZINB mixed model (ZINBMM) with random parameters for traffic density and residential/employment variables n the conditional portion of the model, grouped by CSA, to better address unobserved heterogeneity:

$$\beta_t = \beta + \omega_{i,g} \quad (10)$$

where $\omega_{i,g}$ is a random term for group g.

All models were fit using Laplace approximation as implemented in the R package glmmTMB (Brooks et al., 2017). Variables were retained in each model if they were significant at the 90% level, reduced the model Akaike Information Criterion (AIC), and had a variance inflation factor (VIF) of 10 or less. One exception was made for the VIF criteria for the activity diversity index, which is derived from other variables in the model and is likely somewhat correlated with those variables but has a demonstrated effect on walking behaviors (Ewing and Cervero, 2010). Finally, average marginal effects were estimated using the finite difference method with Monte Carlo simulation (n=2,000 repetitions) to estimate confidence intervals (Cameron and Trivedi, 2009):

$$AME_x = \frac{y_2 - y_1}{\Delta} \quad (11)$$

where AME_x is the average marginal effect for a one-unit change in variable x, y_1 is a vector of predicted values for the dataset, y_2 is a vector of predicted values for a dataset with increased by Δ, and Δ is the standard deviation of variable x divided by 1,000.

3. RESULTS

3.1 Urban Model

Overall, the ZINBMM outperformed the ZINB and NB urban models (Table 2). Focusing on the ZINBMM, transportation system characteristics have significant associations in the logit and conditional portions of the urban model. A 10,000 VMT/mi^2 increase in traffic density on non-access-controlled principal arterials is associated with 124% increase in the likelihood that a tract will not be classified as an always-zero tract (Table 2). Similar associations exist between pedestrian fatalities and traffic density on other facility types, but with lower magnitude. A 10,000 VMT/mi^2 increase in traffic density on interstates, freeways, and expressways is associated with a 30% increase in the likelihood that a tract will be classified as an always-zero tract for, a 101% increase for minor arterials, and a 47% increase for major and minor collectors.

Traffic density is also positively associated with pedestrian fatalities in the count portion of the ZINBMM. A 10,000 VMT/mi^2 increase in traffic density on non-access-controlled principal arterials associated with a 8.8% increase in pedestrian fatalities (Table 2, conditional model). A 10,000 VMT/mi^2 increase in traffic on interstates, freeways, and expressways, minor arterials, and major collectors are associated with a 1.2%, 4.6%, and 2.8%, increases in pedestrian fatality counts, respectively.

Variables characterizing the density of the built environment have significant associations with pedestrian fatality risks. The density of retail employment is associated with increased likelihood that a tract will be classified as a not-always-zero tract. The density of office, industrial, and general services jobs affect the likelihood of being classified as an always-zero tract in the opposite direction—a 1-unit change in the square root of hundreds of office jobs/mi^2 reduces the likelihood of being classified as a not-always-zero tract by 12%, 15%, and 6%, respectively. Effects of general services and entertainment and food/accommodation services employment density in the conditional model are small, yet statistically significant. In not-always-zero tracts, a 1,000 person/mi^2 increase in residential population density is associated with a 0.6% reduction in expected pedestrian fatality counts. (Table 2).

Remaining built environment variables have mixed associations with pedestrian fatality risks. A 10-unit increase in the activity diversity index is associated with a 4.6% increase in expected pedestrian fatality counts. The densities of auto-oriented and multimodal intersections are associated with 34% and 4.1% increases in the likelihood that an urban tract will be classified a not-always-zero tract, respectively. Finally, a 1% increase in the percentage of workers who take transit to work is associated with a 8.9% increase in the likelihood that an urban tract will be classified a not-always-zero tract (Table 2).

3.2 Rural Model

The ZINBMM model provides superior fit compared to ZINB and NB models for rural tracts (Table 3). Traffic density has significant associations with pedestrian fatality risk in the logit and conditional portions of the ZINBMM. Interestingly, these effects are less variable across roadway functional classifications as compared to the urban ZINBMM and are much stronger in the logit of the model relative to the conditional stage of the model. A 1,000 VMT/mi^2 increase in traffic density on interstates, freeways, and expressways is associated with a seven-fold increase in the likelihood that a tract will not be classified as an always-zero tract. A 1,000 VMT/mi^2 increase in traffic density on non-access-controlled principal arterials, minor arterials, and major collectors is associated with 430%, 290%, and 260% increases in the likelihood that a tract will not be classified as an always-zero tract, respectively (Table 3).

In not-always-zero tracts, traffic density is associated with slight increases in expected pedestrian fatality counts. A 1,000 VMT/mi^2 increase in traffic density on interstates, freeways, and expressways is associated a 2.3% increase in expected pedestrian fatality counts (Table 3, conditional model). On non-access-controlled principal arterials, minor arterials, and major collectors, a 1,000 VMT/mi^2 increase in traffic density is associated with 6.5%, 3.8%, and 6.2% increases in pedestrian fatalities, respectively (Table 3, conditional model).

Employment density in entertainment and food/accommodation services and general services sectors is associated with lower likelihood that a rural tract will be classified as a not-always-zero tract while retail employment density is associate with increased likelihood that a rural tract will be classified as a not-always-zero tract, while retail employment is associated with a 8% increase in likelihood (Table 3). A 10-unit increase in the activity mix index is associated with a 7.1% increase in pedestrian fatalities in the conditional model while employment in all sectors aside from entertainment and food/accommodation services is associated with reduced risk (Table 3).

	NB Model		ZINB Model		ZINBMM	
	Odds ratio	t-stat	Odds ratio	t-stat	Odds ratio	t-stat
VMT density *(ten thousand VMT/mi²)*						
Interstates, freeways, and expressways (FC1&2)	1.011	13.63***	1.008	10.18***	1.012	7.53***
Standard deviation of parameter density function					*0.007*	
Principal arterials, non-access-controlled (FC3)	1.075	24.21***	1.055	18.31***	1.088	12.7***
Standard deviation of parameter density function					*0.031*	
Minor arterials (FC4)	1.074	13.54***	1.047	8.57***	1.046	4.72**
Standard deviation of parameter density function					*0.038*	
Major collectors (FC5&6)	1.041	4.54***	1.018	2.04*	1.028	2.48***
Standard deviation of parameter density function					*0.020*	
Employment density *(hundred employees/mi²)*						
General services [a]	0.989	-7.44***	0.993	-4.84***	0.985	-4.64***
Standard deviation of parameter density function					*0.008*	
Entertainment and food/accommodation services	1.001	3.70***	1.001	4.19***	1.001	3.64***
Residential population density *(thousand persons/mi²)*	0.993	-6.79***	0.992	-7.61***	0.994	-1.95***
Activity mix index *(unitless; per 10-point increase)*	1.101	21.68***	1.062	13.03***	1.046	6.90***
Standard deviation of parameter density function					*0.023*	
Median household income *(thousand USD)*	0.989	-19.63***	0.990	-19.04***	0.990	-19.4***
Race/ethnicity						
Percent non-Hispanic Black	1.011	22.32***	1.009	18.53***	1.009	17.9***
Percent non-Hispanic	1.011	19.66***	1.010	17.49***	1.010	17.0***
Percent non-Hispanic Asian	1.008	7.35***	1.006	6.01***	1.006	5.85***
Percent non-Hispanic Other	1.017	5.27***	1.015	4.62***	1.015	4.81***
Age/sex distribution						
Percent female, 45-54	0.989	-2.19*	0.982	-3.53***	0.983	-3.33***
Percent female, 55-64	0.992	-1.36	0.987	-2.33*	0.989	-2.06*
Percent female, 65+	0.991	-2.76**	0.990	-3.17*	0.992	-2.72**
Percent male, 18-24	0.990	-4.13***	0.991	-3.89***	0.991	-3.82***
Percent male, 45-54	1.010	2.25*	1.017	3.54***	1.016	3.46***
Percent male, 55-64	1.019	3.39***	1.022	4.07***	1.021	3.89***
Percent male, 65+	1.007	1.76^	1.010	2.56*	1.008	2.22*
Constant	-2.423	-29.74***	-1.918	-22.51***	-1.951	-21.9***
Zero-accident state						
VMT density *(ten thousand VMT/mi²)*						
Interstates, freeways, and expressways (FC1&2)			1.294	-4.79***	1.303	-4.48***
Principal arterials, non-access-controlled (FC3)			2.263	-11.26***	2.239	-9.56***
Minor arterials (FC4)			1.827	-7.71***	2.008	-7.24***
Major collectors (FC5&6)			1.454	-4.10***	1.467	-3.59***
Employment density *(hundred employees/mi²)*						
Office [a]			0.911	3.24**	0.884	2.41*
Retail [a]			1.907	-4.77***	2.229	-4.75***
Industrial [a]			0.834	3.91***	0.845	1.90^
General services [a]			0.942	2.40*	0.939	1.94^
Intersection density *(count/mi²)*						
Auto-oriented intersections			1.281	-3.65***	1.341	-3.70***
Non-auto-oriented intersections			1.038	-5.20***	1.041	-4.83***
Percent take transit to work			1.076	-3.12**	1.089	-2.82**
Constant			1.663	3.38***	1.678	3.18**
$LL(0)$	-39,636.2		-39,636.2		-39,636.2	
$LL(\boldsymbol{\beta})$	-36,674.3		-36,198.2		-36,127.5	
AIC	73,396.5		72,570.4		72,440.9	
Vuong test statistic (versus NB)			3.83**		4.59**	
N	50,027		50,027		50,027	
Nageilkerke R^2	0.14		0.16		0.17	

[a] Variable is square-root transformed ***$p<0.001$ **$p<0.01$ *$p<0.05$ ^$p<0.10$

Table 2. Pedestrian Fatality Model Estimated Odds Ratios, Urban Tracts

	NB Model		ZINB Model		ZINBMM	
	Odds ratio	t-stat	Odds ratio	t-stat	Odds ratio	t-stat
VMT density *(thousand VMT/mi^2)*						
Interstates, freeways, and expressways (FC1&2)	1.024	10.09***	1.020	9.74***	1.023	8.31***
Standard deviation of parameter density function					*0.008*	
Principal arterials, non-access-controlled (FC3)	1.075	13.0***	1.059	11.2***	1.065	10.8***
Standard deviation of parameter density function					*0.013*	
Minor arterials (FC4)	1.035	4.23***	1.022	3.81***	1.038	3.03**
Standard deviation of parameter density function					*0.060*	
Major collectors (FC5)	1.086	5.22***	1.056	3.49***	1.062	3.76***
Employment density *(employees/mi^2)*						
Office [a]	0.875	-3.81***	0.889	-3.51***	0.874	-3.33***
Standard deviation of parameter density function					*0.044*	
Retail	0.998	-2.00*	0.998	-2.19*	0.999	-1.83^
Industrial [a]	0.917	-4.48***	0.934	-3.77***	0.927	-3.82***
Standard deviation of parameter density function					*0.027*	
General services [a]	0.918	-3.86***	0.948	-2.46*	0.926	-3.02**
Standard deviation of parameter density function					*0.051*	
Entertainment and food/accommodation service	1.001	2.27*	1.002	3.53***	1.002	2.88**
Activity mix index *(unitless)*	1.117	11.8***	1.076	7.78***	1.071	6.48***
Standard deviation of parameter density function					*0.025*	
Intersection density *(count/mi^2)*						
Auto-oriented intersections	1.211	3.87***	1.132	2.76**	1.134	2.62**
Non-auto-oriented intersections	1.044	3.75***	1.030	2.69**	1.024	2.08*
Median household income *(thousand USD)*	0.994	-6.00***	0.993	-7.21***	0.993	-7.40***
Race/ethnicity						
Percent non-Hispanic Black	1.006	5.19***	1.007	6.23***	1.007	6.18***
Percent non-Hispanic	1.007	5.52***	1.008	6.29***	1.008	6.26***
Percent non-Hispanic Other	1.014	9.95***	1.013	8.35***	1.013	8.21***
Age/sex distribution						
Percent younger than 18	1.016	4.51***	1.009	2.66**	1.007	2.10*
Percent 18-24	1.013	3.68***	1.010	2.85**	1.009	2.51*
Percent 25-34	1.023	4.78***	1.017	3.64***	1.017	3.45***
Percent 35-44	1.026	4.15***	1.017	2.70**	1.015	2.36*
Percent 55-65	1.021	3.43***	1.016	2.62**	1.012	1.88^
Percent male	0.988	-3.57***	0.991	-2.59**	0.989	-3.01***
Constant	-3.281	-13.7***	-2.843	-11.5***	-2.594	-10.4***
Zero-accident state						
VMT density *(thousand VMT/mi^2)*						
Interstates, freeways, and expressways (FC1&2)			7.552	-4.89***	7.346	-4.98***
Principal arterials, non-access-controlled (FC3)			4.041	-6.64***	4.225	-6.79***
Minor arterials (FC4)			2.957	-5.18***	2.929	-4.93***
Major collectors (FC5)			2.440	-3.94***	2.620	-4.03***
Employment density *(employees/mi^2)*						
Retail			1.082	-2.99**	1.083	-2.72**
General services [a]			0.454	4.16***	0.468	3.89***
Entertainment and food/accommodation service			0.991	3.32***	0.991	2.98**
Percent walk to work			0.972	2.22*	0.972	2.20*
Tribal land; *1 if >33% of tract in tribal area, 0 otherwise*			4.195	-3.70***	4.252	-3.86***
Constant			1.841	3.81***	1.896	3.89***
$LL(0)$	-16,225.5		-16,225.5		-16,225.5	
$LL(\boldsymbol{\beta})$	-15,194.1		-14,916.2		-14,897.6	
AIC	30,440.2		30,004.4		29,981.1	
Vuong test statistic (versus NB)			2.48**		2.48**	
N	22,711		22,711		22,711	
Nageilkerke R^2	0.11		0.14		0.15	

[a] Variable is square-root transformed ***$p<0.001$ **$p<0.01$ *$p<0.05$ ^$p<0.10$

Table 3. Pedestrian Fatality Model Estimated Odds Ratios, Rural Tracts

3.3 Average Marginal Effects

Because it can be difficult to interpret the overall effects of coefficients in zero-infalted models, we calculated average marginal effects to illustrate how sensitive our pedestrian fatality risks estimates are to changes in traffic density and land use within a tract. Traffic on non-access-controlled principal arterials and minor arterials pose a particularly strong risk for pedestrians in urban areas: the average marginal effect of a 10,000 VMT/mi^2 increase in traffic density is nearly five times greater on non-access-controlled principal arterials and four times greater on minor arterials than on interstates, expressways, and other freeways in urban areas. Increases in VMT density on major and minor collectors have intermediate effects, but are not significantly different from increases in VMT on interstates, freeways, and expressways. Interestingly, the average marginal effect of a 1,000 VMT/mi^2 increase in traffic density in rural tracts does not vary significantly across roadway functional classifications (Figure 2, Table 4).

	Urban Model	Rural Model
VMT density *(per ten thousand VMT/mi^2)* [a]		
Interstates, freeways, and expressways	0.19 *(0.13–0.28)*	0.48 *(0.21–1.1)*
Principal arterials, non-access controlled	0.91 *(0.66–1.3)*	0.40 *(0.18–0.83)*
Minor arterials	0.68 *(0.46–1.0)*	0.30 *(0.13–0.64)*
Major collectors	0.34 *(0.15–0.58)*	0.28 *(0.12–0.60)*
Population density *(per thousand persons/mi^2)*	-0.035 *(-0.055– -0.020)*	-
Employment density *(per hundred jobs/mi^2)* [b]		
Office	-0.11 *(-0.23– -0.020)*	-0.056 *(-0.14– -0.016)*
Retail	1.68 *(0.90–2.72)*	0.017 *(0.0030–0.043)*
Industrial	-0.22 *(-0.53–0.0055)*	-0.038 *(-0.091– -0.014)*
General services	-0.083 *(-0.17– -0.026)*	-0.091 *(-0.22– -0.034)*
Entertainment and food/accommodation service	0.0066 *(0.0028–0.012)*	-0.0004 *(-0.0029–0.0016)*
Activity mix index *(unitless; per 10-unit change)*	0.38 *(0.24–0.60)*	0.070 *(0.030–0.16)*
Intersection density *(count/mi^2)*		
Auto-oriented intersection	0.13 *(0.062–0.23)*	0.12 *(0.025–0.30)*
Non-auto-oriented intersections	0.018 *(0.010–0.031)*	0.022 *(0.0015–0.065)*

[a] Per thousand VMT/mi^2 in rural model [b] Per job/mi^2 in rural model

Table 4. Average marginal effects of traffic, population, and employment density variables on pedestrian fatality rate (annual rate per 100,000 persons)

Average marginal effects reveal particularly strong associations between pedestrian fatalities and employment density in certain sectors. In urban and rural tracts, positive associations are seen between employment in the retail sector and pedestrian fatalities. In urban tracts, a positive association is also seen between pedestrian fatalities and entertainment and food/accommodation services employment while negative associations are seen for office and general services employment and residential population density (Figure 2, top right; Table 4). In rural tracts, negative associations are seen between office industrial, and general services employment and pedestrian fatalities. while residential population density and employment in other sectors have negatively associations (Figure 2, bottom right; Table 4). The activity mix index is associated with elevated risk in both urban and rural tracts.

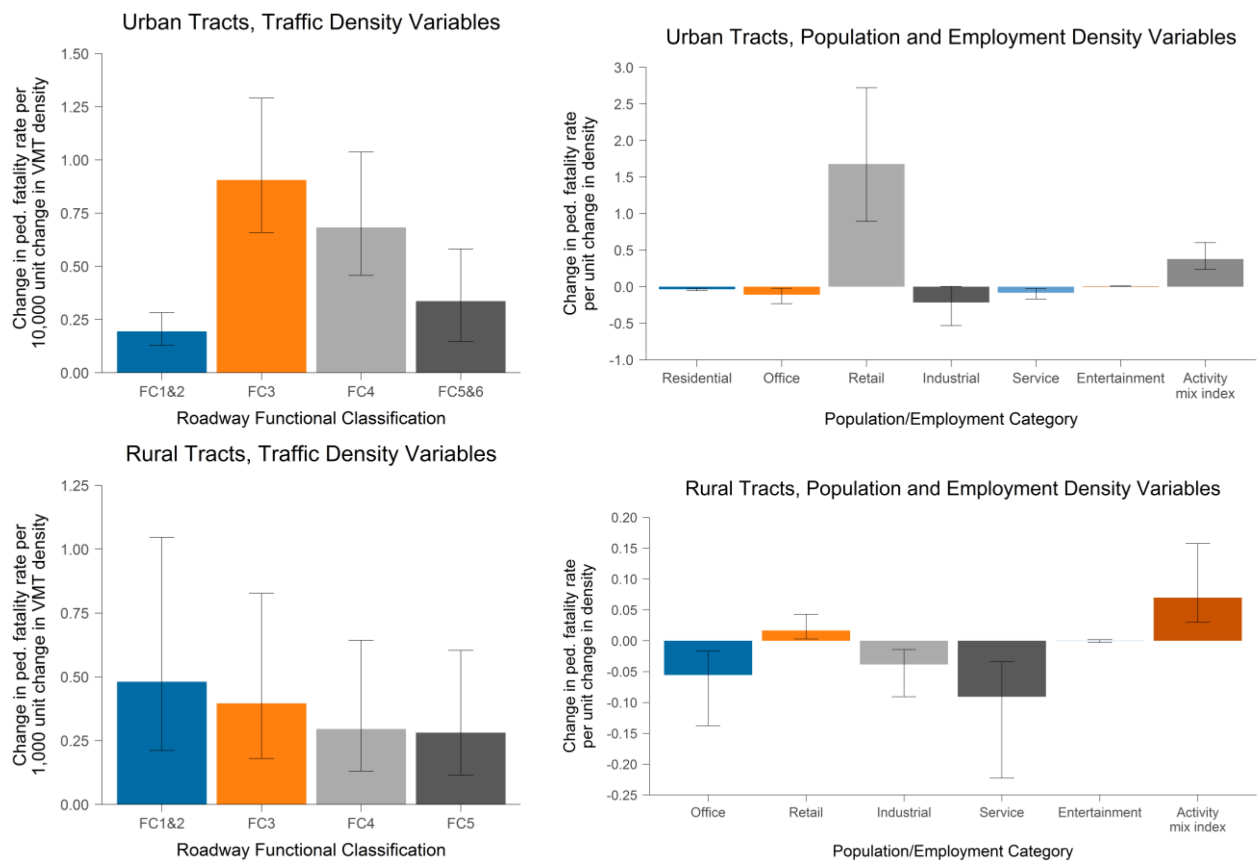

Figure 2. Average marginal effects of traffic density (left) and population and employment density (right) variables on pedestrian fatality rates (annual fatalities per 100,000 persons) for urban (top) and rural (bottom) tracts. Whisker lines show 95% confidence intervals.

3.4 Comparison to Los Angeles High Injury Network

To illustrate how the model developed in this paper could complement existing tools, we compared how well our model performed relative to the city of Los Angeles' High Injury Network (HIN). Los Angeles developed the HIN as a component of their Vision Zero strategy and was recently identified as a focus city for pedestrian safety by FHWA (Federal Highway Administration, 2015; Vision Zero Los Angeles, 2017). The HIN was developed by first weighting all injuries that occurred between 2009–2013 based on injury severity, with higher weights assigned to pedestrians and cyclists injuries. Weighted injuries were then assigned to intersections and corridors to develop the HIN (Vision Zero Los Angeles, 2017).

To compare our model estimates to the HIN, we classified all observed pedestrian fatalities from 2012-2016 that occurred within 200 feet of the HIN as "identified by HIN". We then classified all fatalities that occurred in high-risk tracts, defined as tracts in the highest quintile of estimated risk nationally, as "in high-risk tract." Out of 489 pedestrian fatalities, 322 (66%) were identified by the HIN and 301 (62%) occurred in high-risk tracts. Further, 209 (43%) were identified by both models (Figure 3, blue circles), 92 (19%) were identified by our model but not the HIN (white circles), 113 (23%) were identified by the HIN but not our model (yellow circles), and 75 (15%) were not identified by either method (red circles). Blue circles are clustered in certain neighborhoods and yellow circles in others, indicating that each approach has advantages in certain contexts. Thus, our model identifies high-risk neighborhoods about as well as an HIN; applied in conjunction with an HIN, our model could identify additional high-risk neighborhoods. While differences in methods used to develop the HIN and our model preclude a true apples-to-apples comparison, this comparison, this comparison highlights the usefulness of employing differing approaches to identify pedestrian environments with elevated risks.

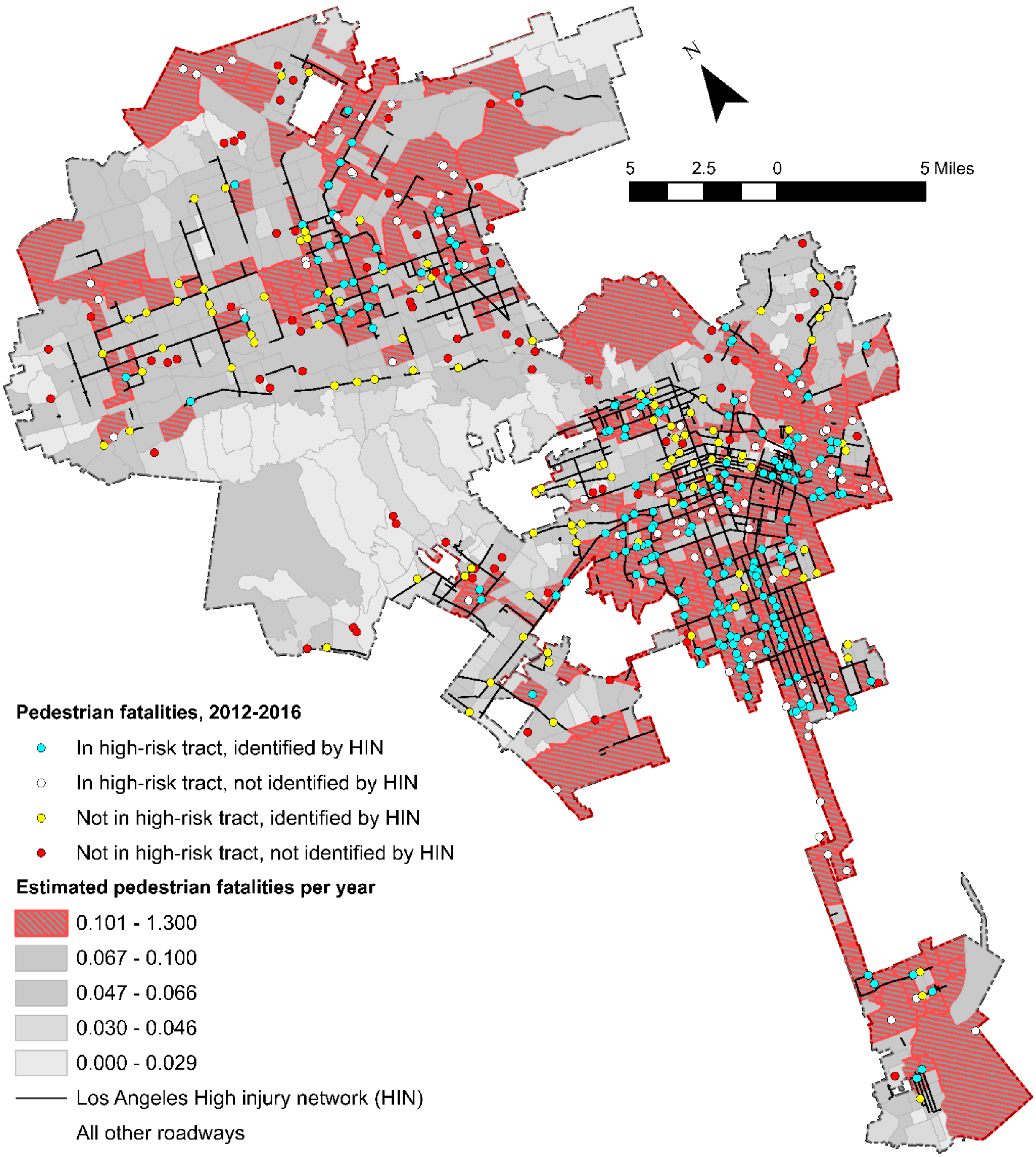

Figure 3. Comparison of estimated high-risk tracts (red hatching) with the Los Angeles HIN (black lines). Clusters of blue dots show neighborhoods where our model better matches observed pedestrian fatalities; clusters of yellow dots show neighborhoods where the HIN better matches observed fatalities.

4. DISCUSSION

We performed the first national-scale analysis of the associations between tract-level pedestrian fatalities, traffic, built environment, and sociodemographic characteristics at the national scale. We found especially strong associations between traffic on non-access-controlled principal arterials and pedestrian fatalities in urban tracts. While it is known that the plurality of pedestrian fatalities occurs on urban arterials, it can be difficult to determine how urban arterials impact pedestrian fatality risk independent of their context (Federal Highway Administration, no date). By including sociodemographic and built environment variables alongside traffic data, we can better understand the contributions of a roadway's land-use and sociodemographic context on pedestrian fatality risks, thereby supporting a more targeted approach to reducing pedestrian fatalities on urban arterials. Interestingly, we did not find that non-access-controlled principal arterials are more dangerous than other roadways in rural contexts.

In urban tracts, we found positive associations between pedestrian fatality risk and employment in the retail and entertainment and food/accommodation services sectors. Pedestrian activity is likely higher in neighborhoods with greater retail, dining, and entertainment activity. Further, these neighborhoods may also be associated with higher prevalence of risky behaviors, such as walking and/or driving while intoxicated. In rural tracts, we found positive associations with retail employment and negative associations with employment in other categories, potentially indicating that retail districts may pose unique risks to pedestrians in rural contexts.

Overall, our findings are aligned with and build on existing findings in the literature. By combining characteristics of facility-scale studies (e.g., traffic density by functional classification) and neighborhood-scale studies (e.g., employment density be sector) we help unify previous findings towards a systemic, risk-based approach to pedestrian safety. Further, consistent national findings bolster the external validity of previous studies conducted over smaller spatial scales (Abdel-Aty et al., 2013; Cottrill and Thakuriah, 2010; Das and Sun, 2015; Noland and Quddus, 2004). Looking forward, our work may support further integration of facility- and neighborhood-scale studies within a scalable and generalizable pedestrian fatality risk framework (Turner et al., 2017).

This research can help support data-driven, evidence-based transportation decision-making at the Federal, state, and local levels. The model developed in this paper could be applied as a screening tool to identify high-risk tracts. In jurisdictions with limited resources, this model could be applied as a screening tool to identify high-risk Census tracts and help inform resource allocation decisions prospectively, rather than in reaction to patterns of past fatalities that may not adequately characterize underlying risks given their relative infrequency. In jurisdictions that have established pedestrian safety programs, this model could be used to identify high-risk neighborhoods that may not be identified using other tools, such as HINs. This model could also support forward-looking estimates of how pedestrian fatality risks may change given changes in the transportation system and/or built environment, such as shifts in traffic patterns due to new developments or investments in alternative transportation modes. Finally, this model could be applied to develop baseline pedestrian fatality risks across a region to support cost-effectiveness and/or benefit-cost estimations of countermeasures selected via resources such FHWA's Pedestrian Safety Guide and Countermeasure Selection System or AASHTO's Guide for the Planning, Design, and Operation of Pedestrian Facilities (American Association of State Highway and Transportation Officials, 2004; Federal Highway Administration, no date).

This work has several methodological limitations. First, while we include grouped random parameters in the conditional portion of our ZINBMMs, more robust application of random parameters models may better account for unobserved heterogeneity not addressed in our approach (Anastasopoulos, 2016). While our regression parameters were relatively stable after the introduction of grouped random parameters, remaining unobserved heterogeneity may bias regression coefficients. Other approaches, such as latent class modeling and spatial autocorrelation modeling, have also been used to address unobserved heterogeneity, but we are not aware of applications of such techniques to national-scale models with small a spatial unit of analysis (Behnood and Mannering, 2016). Future work should assess the validity of such models when applied at the national scale to further account for unobserved heterogeneity and test the robustness of our results.

The scarcity of data at the national scale in several key areas presented limitations to our work. Pedestrian volumes are not routinely tracked nationally, making it difficult to characterize exposure in assessments of pedestrian fatality risk. New data sources, such as passively collected cell phone data, may help transportation researchers and practitioners characterize pedestrian volumes in the future. Additionally, non-fatal pedestrian injuries are not consistently tracked nationally, leading to many tracts with zero fatalities due to left-censoring of pedestrian injury data. Finally, roadway characteristics related to the quality of the pedestrian environment, such as the presence and quality of sidewalks and street crossings, are not available nationally. Integration of roadway characteristics such presence of sidewalks into databases such as the HPMS support further research to better understand of pedestrian fatality risks and the extent to which countermeasures improve pedestrian safety.

5. CONCLUSIONS

We used ZINBMM to identify the effects of transportation system, built environment, and sociodemographic characteristics on pedestrian fatality in urban and rural contexts at the national scale. Particularly strong associations were found between traffic on non-access-controlled principal arterials in urban areas as well as employment density in the retail sectors in urban and rural contexts. In regions that do not have well-established pedestrian safety programs, the model developed in this paper could be applied by transportation practitioners to characterize pedestrian fatality risks and support targeted, data-driven pedestrian fatalities interventions. In contexts where pedestrian safety programs are more advanced, this model could be applied in conjunction with existing tools, such as HINs, to more fully characterize high-risk areas. More broadly, this work is a step towards prospective, risk-based frameworks. These frameworks are better suited for applications such as supporting cost-benefit analysis or estimating how decisions that shape the built environment may influence pedestrian fatality risks than retrospective methods that rely on patterns of past pedestrian fatalities. The recent increase in pedestrian fatalities in the U.S. calls for integrated, systemic approaches to transportation safety. Prospective risk-based tools, like the one developed in this paper, can help transportation practitioners and policy-makers make evidence-based decisions on how to best allocate resources to reduce pedestrian fatalities in the US.

6. ACKNOWLEDGEMENTS

We would like to thank Tianjia Tang, Gabe Rousseau, and Dan Goodman at FHWA; Ruth Esteban, Chou-Lin Chen and Tim Pickrell at NHTSA; Bob Schneider at UW-Milwaukee; and Gary Baker, Alex Olberg, and David Perlman at Volpe for their valuable contributions.

Funding: This paper was supported in part by an appointment to the Research Participation Program at the Office of the Under Secretary for Policy, USDOT, administered by ORISE through an interagency agreement between the US DOE and USDOT.

REFERENCES

Abdel-Aty, M., J. Lee, C. Siddiqui, and K. Choi. (2013). Geographical unit based analysis in the context of transportation safety planning. *Transportation Research Part A*, *49*, 62–75. https://doi.org/10.1016/j.tra.2013.01.030

Amoh-Gyimah, R., M. Saberi, and M. Sarvi. (2016). Macroscopic modeling of bicycle and pedestrian bicycle crashes: A cross-comparison of estimation methods. *Accident Analysis and Prevention*, *93*, 147–159. https://dx.doi.org/10.1016/j.aap.2016.05.001

American Association of State Highway and Transportation Officials. (2004). *Guide for the Planning, Design, and Operation of Pedestrian Facilities*. AASHTO, Washington, DC.

Anastasopoulos, P. (2016). Random parameters multivariate tobit and zero-inflated count data models: Addressing unobserved and zero-state heterogeneity in accident injury-severity rate and frequency analysis. *Analytic Methods in Accident Research*, *11*, 17–32. https://dx.doi.org/10.1016/j.amar.2016.06.001

Behnood A., and F. Mannering. (2016). An empirical assessment of the effects of economic recessions on pedestrian-injury crashes using mixed and latent-class models. *Analytic Methods in Accident Research*, *12*, 1–17. https://dx.doi.org/10.1016/j.amar.2016.07.002

Brooks, M., K. Kristensen, K. van Benthem, A. Magnusson, C. Berg, A. Nielsen, H. Skaug, M. Machler, and B. Bolker. (2017). glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. *R Journal*, *9*(2), 378-400. https://doi.org/10.3929/ethz-b-000240890

Bunn, F., T. Collier, C. Frost, K. Ker, I. Roberts, and R. Wentz. (2003). Traffic calming for the prevention of road traffic injuries: systematic review and meta-analysis. *Injury Prevention*, *9*(3), 200–204. https://dx.doi.org/10.1136/ip.9.3.200

Cameron A., and P. Trivedi. (2013). *Regression Analysis of Count Data*. Cambridge University Press, New York.

Cameron A., and P. Trivedi. (2009). *Microeconometrics using Stata*. Stata Press, College Station.

Census Bureau. (2016a). American Community Survey 5-year Estimates [B01001, B03002, B08301, B19013, B25003; 2012–2015]. https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml. Accessed July 20, 2017.

Census Bureau. (2016b). Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics [wac, od; 2012–2015]. https://lehd.ces.census.gov/data/lodes/LODES7/. Accessed July 20, 2017.

Census Bureau Urban Area Criteria for the 2010 Census. (2011). 76 Fed. Reg. 53030. *Federal Register: The Daily Journal of the United States, 76*, 53030–53043.

Census Bureau. No date. *Calculating Daytime Population Estimates*. https://www.census.gov/hhes/commuting/data/calculations.html. Accessed July 20, 2017.

Cervero, R., and K. Kockelman. (1997). Travel demand and the 3Ds: density, diversity, and design. *Transportation Research Part D, 2*(3), 199–219. https://doi.org/10.1016/S1361-9209(97)00009-6

Cohen, A., and L. Einav. (2003). The effects of mandatory seat belt laws on driving behavior and traffic fatalities. *The Review of Economics and Statistics, 85*(4), 828–843. https://doi.org/10.1162/003465303772815754

Conway, A., J. Cheng, D. Peters, and N. Lownes. (2013). Characteristics of Multimodal Conflicts in Urban On-Street Bicycle Lanes. *Transportation Research Record, 2387*, 93–101. https://doi.org/10.3141/2387-11

Cottrill, C., and P. Thakuriah. (2010). Evaluating pedestrian crashes in areas with high low-income or minority populations. *Accident Analysis and Prevention*, *42*(6), 1718–1728. https://doi.org/10.1016/j.aap.2010.04.012

Das, S., and X. Sun. (2015). Factor Association with Multiple Correspondence Analysis in Vehicle–Pedestrian Crashes. *Transportation Research Record, 2519*, 95–103. https://dx.doi.org/10.3141/2519-11

Dong, C., D. Clarke, X. Yan, A. Khattak, and B. Huang. (2014). Multivariate random-parameters zero-inflated negative binomial regression model: An application to estimate crash frequencies at intersections. *Accident Analysis and Prevention*, *70*, 302–329. https://dx.doi.org/10.1016/j.aap.2014.04.018

Environmental Protection Agency. (2013). Smart Location Database. http://www.arcgis.com/home/item.html?id=137d4e512249480c980e00807562da10. Accessed July 20, 2017.

Ewing, R. and R. Cervero. (2010). Travel and the built environment. *Journal of the American Planning Association*, *76*(3), 265–294. https://doi.org/10.1080/01944361003766766

Federal Highway Administration. (2016a). Highway Performance Monitoring System [2012–2015]. https://www.fhwa.dot.gov/policyinformation/hpms/shapefiles.cfm. Accessed July 20, 2017.

Federal Highway Administration. (2016b). *Highway Performance Monitoring System Field Manual*. https://www.fhwa.dot.gov/policyinformation/hpms/fieldmanual/hpms_field_manual_dec2016.pdf. Accessed July 20, 2017.

Federal Highway Administration. (no date). *Pedestrian-Bicycle Focus Cities/States 2015*. https://safety.fhwa.dot.gov/ped_bike/ped_focus/focus_cities_states2015.cfm. Accessed July 20, 2017.

Federal Highway Administration. (no date). *National fatalities between 2010 and 2014*. https://rspcb.safety.fhwa.dot.gov/Dashboard/Default.aspx. Accessed July 20, 2017.

Federal Highway Administration. (no date). *Pedestrian Safety Guide and Countermeasure Selection System*. http://www.pedbikesafe.org/pedsafe/. Accessed July 20, 2017.

Federal Highway Administration (2013). *Highway Functional Classification Concepts, Criteria and Procedures*. Publication FHWA-PL-13-026. FHWA, USDOT.

Freeland A., S. Banerjee, A. Dannenberg, and A. Wendel. (2013). Walking associated with public transit: moving toward increased activity in the United States. *Am J Public Health*, *103*(3), 536–42. https://doi.org/10.2105/AJPH.2012.300912

Jacobsen, P. (2003). Safety in numbers: More walkers and bicyclists, safer walking and bicycling. *Injury Prevention, 9,* 205–209. https://doi.org/10.1136/ip.9.3.205

Johansson, R. (2009). Vision zero – Implementing a policy for traffic safety. *Safety Science*, *47*, 826–831. https://doi.org/10.1016/j.ssci.2008.10.023

Lyons, W., L. Morse, L. Nash, and R. Strauss. (2014). *Statewide transportation planning for healthy communities*. Publication FHWA-HEP-14-028. Volpe, USDOT.

Mannering, F. and C. Bhat. (2014). Analytic methods in accident research: Methodological frontier and future directions. *Analytic Methods in Accident Research*, *1,* 1–22. https://doi.org/10.1016/j.amar.2013.09.001

Mansfield, T., and J. MacDonald Gibson. (2016). Estimating active transportation behaviors to support health impact assessment in the United States. *Frontiers in Public Health, 4*, 63. https://doi.org/10.3389/fpubh.2016.00063

Moving Ahead for Progress in the 21st Century Act. (2012). Pub. L. 112–141. 126 Stat. 405.

National Center for Statistics and Analysis (2017a). *Traffic Safety Facts 2015*. Publication DOT-HS-812-384. NHTSA, USDOT.

National Center for Statistics and Analysis (2017b). *Pedestrians: 2015 data*. Publication DOT-HS-812-375. NHTSA, USDOT.

National Highway Traffic Safety Administration. (2017). Fatality Analysis Reporting System [2012–2016]. ftp://ftp.nhtsa.dot.gov/fars/. Accessed July 20, 2017.

Sarwar, M., G. Fountas, C. Bentley, P. Anastasopoulos, A. Blatt, J. Pierowicz, K. Majka, and R. Limoges. (2017). Preliminary investigation of the effectiveness of high-visibility crosswalks on pedestrian safety using crash surrogates. *Transportation Research Record*, *2659*, 182–191. https://dx.doi.org/10.3141/2659-20

Singh, H., M. Siahpush, and M. Kogan. (2010). Neighborhood socioeconomic conditions, built environments, and childhood obesity. *Health Affairs*, *29*, 503–512. https://dx.doi.org/10.1377/hlthaff.2009.0730

Singleton, P., and K. Clifton. (2017). Considering health in US metropolitan long-range transportation plans: A review of guidance statements and performance measures. *Transport Policy*, *67*, 79–89. https://doi.org/10.1016/j.tranpol.2017.02.003

Turner, S., I. Sener, M. Martin, S. Das, E. Shipp, R. Hampshire, K. Fitzpatrick, L. Molnar, R. Wijesundera, M. Colety, and S. Robinson. (2017). Synthesis of Methods for Estimating Pedestrian and Bicyclist Exposure to Risk at Areawide Levels and on Specific Transportation Facilities. Publication FHWA-SA-17-041. FHWA, USDOT.

Ukkusuri, S., S, Hasan, and H. Abdul Aziz. (2011). Random parameters model used to explain effects of built-environment characteristics on pedestrian crash frequency. *Transportation Research Record*, *2237*, 98–106. https://dx.doi.org/10.3141/2237-11

Vision Zero Los Angeles. (2017). *Vision Zero Los Angeles 2015–2025: Action Plan*. Los Angeles: Los Angeles Department of Transportation.

Whitfield G., P. Paul, and A. Wendel. (2015). Active transportation surveillance – United States, 1999–2012. *MMWR CDC Surveillance Summary*, 6, SS–7.