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Is the safety-in-numbers effect still observed in areas with low pedestrian activities? A case study of a suburban area in the United States☆

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ABSTRACT

In previous studies, the safety-in-numbers effect has been found, which is a phenomenon that when the number of pedestrians or cyclists increases, their crash rates decrease. The previous studies used data from highly populated areas. It is questionable that the safety-in-numbers effect is still observed in areas with a low population density and small number of pedestrians. Thus, this study aims at analyzing pedestrian crashes in a suburban area in the United States and exploring if the safety-in-numbers effect is also observed. We employ a Bayesian random-parameter Poisson-lognormal model to evaluate the safety-in-numbers effects of each intersection, which can account for the heterogeneity across the observations. The results show that the safety-in-numbers effect were found only at 32 intersections out of 219. The intersections with the safety-in-numbers effect have relatively larger pedestrian activities whereas those without the safety-in-numbers effect have extremely low pedestrian activities. It is concluded that just encouraging walking might result in serious pedestrian safety issues in a suburban area without sufficient pedestrian activities. Therefore, it is plausible to provide safe walking environment first with proven countermeasures and a people-oriented policy rather than motor-oriented. After safe walking environments are guaranteed and when people recognize that walking is safe, more people will consider walking for short-distance trips. Eventually, increased pedestrian activities will result in the safety-in-numbers effects and walking will be even further safer.

1. Introduction

Recently, walking and cycling have been encouraged not only because they are economically and environmentally sustainable but also they can improve public health of the society. Thus, many governments and communities have promoted people to use such active modes of transportation, instead of passenger cars. Nevertheless, the high crash risk of the pedestrians and cyclists have been a deterrent for people to select walking and cycling as their major transportation mode. Previous studies also showed that people consider the crash risk as an important factor for walking and cycling (Jacobsen, 2003; Weinstein Agrawal et al., 2008; Jacobsen et al., 2009). Thus, there have been many efforts to identify factors increasing crashes involving vulnerable road users, and suggested countermeasures to improve their safety. Some previous studies have found that when the number of pedestrians or cyclists increases, their crash rates (i.e., the number of crashes involving pedestrians or cyclists per the number of pedestrians or cyclists) decrease (Leden, 2002; Jacobsen, 2003; Zegeer et al., 2005; Geyer et al., 2006; Daniels et al., 2010; Miranda-Moreno et al., 2011; Elvik et al., 2013; Kröyer, 2016; Elvik and Bjørnskau, 2017; Tasic et al., 2017; Xu et al., 2017; Xie et al., 2018). It means that the probability of crash involvements per vulnerable user would be decreased if the number of pedestrians or cyclists increases. This phenomenon is called safety-in-numbers (SIN). There have been difficulties to analyze the SIN effect because the number of pedestrian trips is hard to obtain in the above-mentioned previous studies. For this reason, some used population, population density, or land-use (e.g., residential, commercial) as a surrogate measure for pedestrian trips (Lee, 2014; Lee et al., 2014a, a; Lee et al., 2015b; Cai et al., 2016; Lee et al., 2018).

In the recent two decades, several researchers successfully collected pedestrian trip data and explored the SIN effects. Jacobsen (2003) found the SIN effect for walking and cycling, which means the crash risk of larger number of pedestrians and bicyclists is lower. The author discussed that it can be explained by the fact that the behavior of

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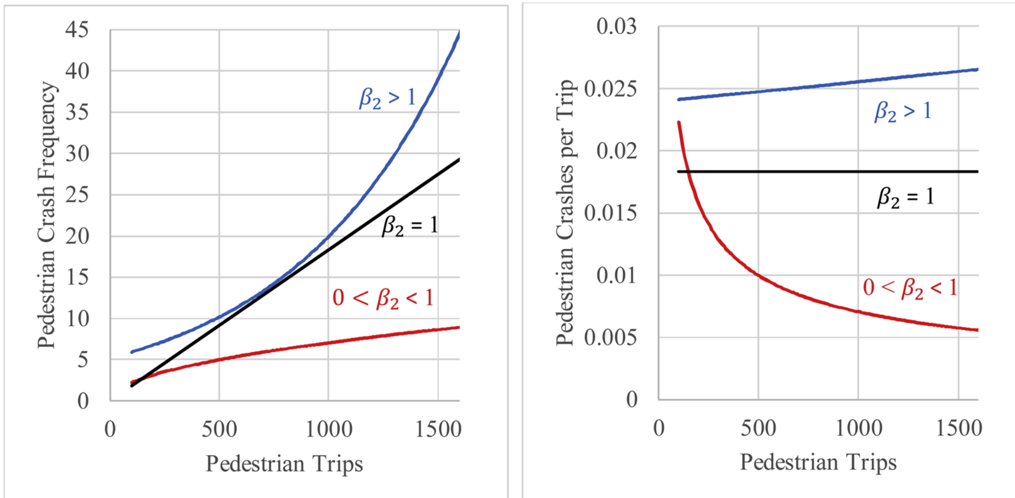

Fig. 1. Graphic description of safety-in-numbers for pedestrian safety.
Data source: 2016 American Community Survey, U.S. Census Bureau

drivers controls the probability of crashes with pedestrians and bicyclists. It indicates that drivers change their behavior in the presence of many pedestrians and bicyclists. Elvik (2017) also argued that if there are many pedestrians or cyclists, drivers would expect to encounter them and interact with them, which could strengthen the SIN effect.

The following equation shows the relationship between the number of pedestrian crashes and vehicle and pedestrian exposure:

$$Y_i = exp^{\beta_0} Veh_i^{\beta_1} Ped_i^{\beta_2} \exp(\beta X_i) \quad (1)$$

where, Y_i is the number of pedestrian crashes, β_0 is the intercept, β_1 is the exponential coefficient of vehicle volume, β_2 is the exponential coefficient of pedestrian trips, β is a vector of parameters to be estimated, and X_i is a vector of independent variables.

Fig. 1 was displayed to explain the concept of the SIN effects using constructed data. In the figure, the shape of the curves is determined by the range of β_2. The left graph of Fig. 1 indicates the relationship between the number of pedestrian crashes and pedestrian trips, and the right graph illustrates the relationship between the pedestrian crash rate (pedestrian crashes per trip) and pedestrian trips. If β_2 is greater than one (blue line), the pedestrian crash rates would increase as pedestrian trips increase. On the other hand, if β_2 is exactly one (black line), the crash rate is constant. Lastly, if β_2 is less than one and greater than zero (red line), the crash rate would decrease as pedestrians increase, which is the SIN effect.

Table 1 summarizes the studies that found the SIN effects for pedestrian safety in the past two decades. Leden (2002) used the pedestrian and vehicle data of 1983–1986 from about 300 signalized intersections in Hamilton, Ontario, Canada. The authors investigated the collisions between pedestrians and left-/right-turning vehicles, and found that the exponential coefficients of pedestrian trips for the collisions with left-turning and right-turning vehicles were 0.33 and 0.48, respectively, and they were statistically significant at 95% confidence level. The finding indicates the existence of the SIN effects. Jacobsen (2003) collected data from multiple countries. First, the author analyzed pedestrian injuries in the year of 2000 in 68 cities in California, and found that the exponential coefficient of pedestrian trips was 0.41 and statistically significant at 95%. Subsequently, the author explored pedestrian injuries of 1993–1996 in 47 Danish towns, the exponential coefficient of pedestrian trips was 0.36 but it did not show a statistical significance. Furthermore, the author studied pedestrian fatalities in eight European countries. Although the exponential coefficient of pedestrian trips was 0.13, it was not statistically significant.

In the study of Zegeer et al. (2005), the authors investigated pedestrian safety at uncontrolled locations with marked and unmarked crosswalks in 28 cities in the United States. The authors found the SIN effects at the locations with marked and unmarked crosswalks, as their exponential coefficients of pedestrian trips were 0.33 and 0.64, respectively. Geyer et al. (2006) used the data from 247 intersections in Oakland, California. The authors also confirmed the presence of the SIN phenomena in their study area. The coefficient of pedestrian trips was 0.61 and statistically significant at 95% confidence level. Daniels et al. (2010) explored the safety performance of 90 roundabouts in Flanders, Belgium. In the authors' pedestrian crash model, the coefficient of pedestrian trips was 0.27 ($p < 0.01$), which indicated the SIN effects at roundabouts. In addition, Schneider et al. (2010) acquired data from 81 intersections in Alameda, California, and found the coefficient of pedestrians, 0.58 which was significant at 95% confidence level.

Miranda-Moreno et al. (2011) investigated the influence of built environment on pedestrian activity using data from 519 intersections in Montreal, Quebec. Along with other significant variables, the coefficient of pedestrian trips, 0.26 was also significant at 95% confidence level. Elvik et al. (2013) examined the factors that influence pedestrian safety in Oslo, Norway. The authors found the evidence of the SIN effect for pedestrians since the coefficient of pedestrian trips was 0.76 and it was statistically significant at 95% confidence level. A recent study of Kröyer (2016) revealed the SIN effects for pedestrians from 113 intersections in six cities in Sweden. The coefficient of pedestrian trips was 0.55 with a statistical significance at 95% confidence level. The author also found that the models with short-term observation periods are less reliable. Most of the previous studies, except for Jacobsen (2003), explored the SIN phenomena at intersections or crosswalks. On the other hand, Tasic et al. (2017) investigated the SIN effect at a macroscopic scale. The authors collected data from 801 census tracts of Chicago, Illinois, and developed generalized additive models. The authors found that the coefficient of pedestrian trips was 0.294 and it was statistically significant at 95% confidence interval, which indicated the SIN for pedestrian safety.

Elvik and Bjørnskau (2017) conducted a meta-analysis of the SIN effects using 26 studies and confirmed that the studies consistently found the existence of SIN phenomena. The authors estimated the regression coefficients from a random-effects inverse-variance meta-analysis for motor vehicle and pedestrian volumes. They were 0.499 and 0.511, respectively and statistically significantly less than one at 95% confidence interval. Xu et al. (2017) used intersection data of 2010–2012 from Hong Kong, and developed a Bayesian Poisson-

Table 1
Studies reporting the safety-in-numbers (SIN) effects in the recent two decades.

Study	Region	Study period	Observations	Outcome measures	Confounders controlled					
					Motor vehicle	Pedestrian	Geometric design	Traffic control	Land use	Demo-graphic
Leden (2002)	Hamilton,Ontario, Canada	1983-1986	749 signalized intersection approaches	Crashes between pedestrians and left-turning vehicles	1.19**	0.33**				
			126 signalized intersection approaches	Crashes between pedestrians and right-turning vehicles	0.86**	0.48**				
Jacobsen (2003)	68 cities in California	2000	68 cities	Pedestrian injuries per capita		0.41** (0.066)				
	47 Danish towns	1993-1996	47 towns	Pedestrian injuries per capita		0.36 (0.235)				
	8 European countries	1998	8 countries	Pedestrian fatalities per capita		0.13 (0.434)				
Zegeer et al. (2005)	28 cities	1994-1998	1000 marked crosswalks	Pedestrian-vehicle crashes	0.99** (0.17)	0.33** (0.06)	✓			
			1000 unmarked crosswalks		0.55** (0.26)	0.64** (0.13)	✓			
Geyer et al. (2006)	Oakland, California	2000-2002	247 intersections	Pedestrian-vehicle crashes	0.15 (0.12)	0.61** (0.12)	✓		✓	
Daniels et al. (2010)	Flanders, Belgium	1996-2004	90 roundabouts	Crashes involving injured pedestrians	2.77**	0.27**	✓			
Schneider et al. (2010)	Alameda, California	1998-2007	81 intersections	Pedestrian-vehicle crashes	1.50** (0.43)	0.58** (0.16)	✓	✓	✓	✓
Miranda-Moreno et al. (2011)	Montreal, Canada	1999-2003	519 signalized intersections	Pedestrian-vehicle crashes	0.90**	0.26**		✓	✓	✓
Elvik et al. (2013)	Oslo, Norway	2004-2008 2006-2010	159 marked pedestrian crossings	Pedestrian-vehicle crashes	0.53** (0.17)	0.76** (0.11)	✓			
Kröyer (2016)	6 cities, Sweden	2008-2012	113 intersections	Pedestrian-vehicle crashes	0.65 (0.53)	0.55** (0.27)	✓			
Tasic et al. (2017)	Chicago, Illinois	2005-2012	801 census tracts	Pedestrian-vehicle crashes	0.049* (0.028)	0.295** (0.036)	✓	✓	✓	✓
Elvik and Bjørnskau (2017)	Multiple areas (meta-analysis)	1979-2014	26 studies	Pedestrian-vehicle crashes	0.499**	0.511**				
Xu et al. (2017)	Hong Kong, China	2010-2012	288 signalized intersections	Pedestrian-vehicle crashes	0.271** (0.078)	0.213** (0.051)	✓	✓		
Xie et al. (2018)	Hong Kong, China	2010-2012	262 signalized intersections	Pedestrian-vehicle crashes	0.27** (0.09)	0.23** (0.05)	✓	✓		

Note: S.D. refers to the standard deviation. In(Leden, 2002), (Daniels et al., 2010) and (Miranda-Moreno et al., 2011), the standard errors of the corresponding coefficients were not reported. ** and * denote statistical significance at the 95% and 90% confidence levels, respectively.

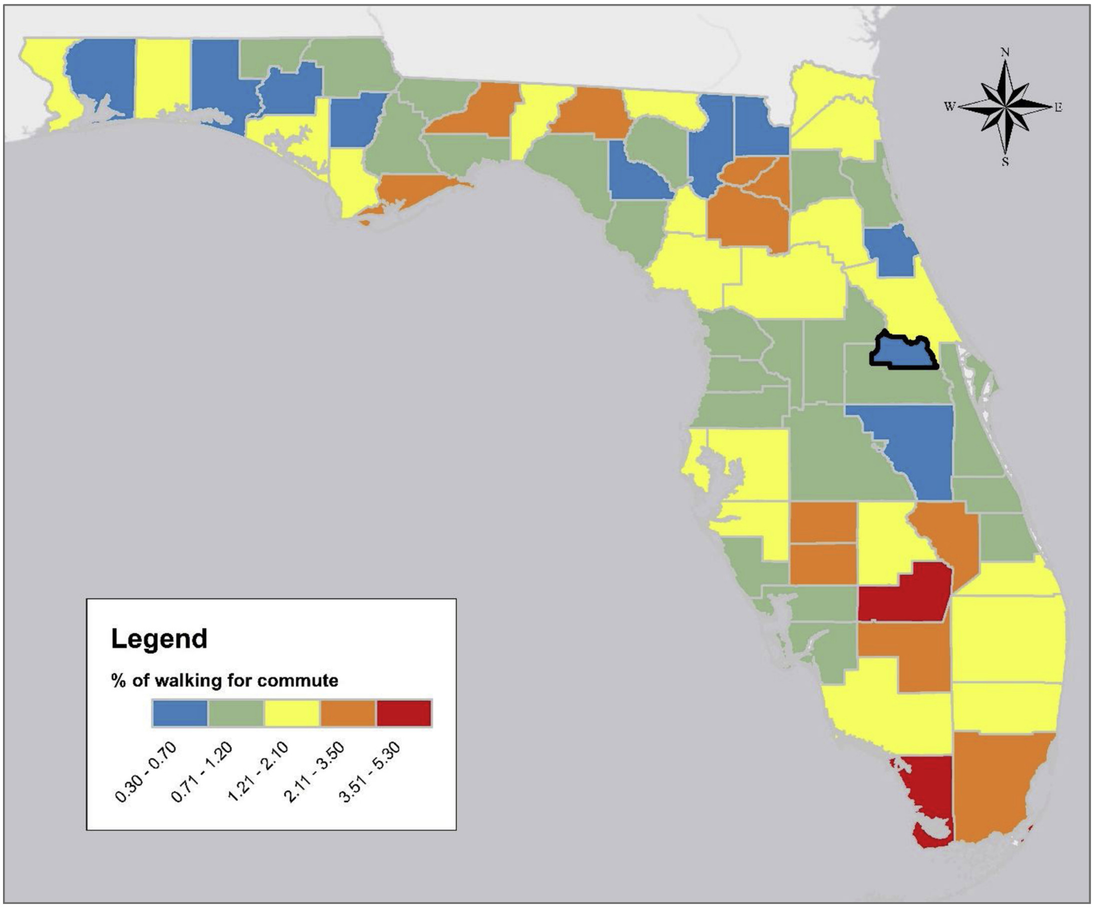

Fig. 2. The percentage of walking commuters in Florida by county (A region marked by a thick black boundary line is Seminole County).

lognormal model for pedestrian crashes. In the modeling results, the authors identified the SIN effects as the coefficient of pedestrian trips was 0.21 with a statistical significance at 95% confidence level. Using the same dataset, Xie et al. (2018) adjusted the measurement errors in pedestrian volumes when modeling pedestrian crash frequency at signalized intersections. Their results also confirmed the significant nonlinear relationship between the number of people crossing at an intersection and the number of crashes involving pedestrians, with an estimated coefficient of 0.23.

As seen in the previous studies, the findings are quite consistent. However, those studies used data from metropolitan areas with a high population density. Therefore, a question arises: is the effects of the safety-in-numbers observed in less populated areas as well? In order to answer the research question, we have collected data from a suburban area in Central Florida of the United States: Seminole County.

In Seminole County, most of the households have at least one available vehicle (96.4%) and very few people choose walking as the commute mode of transportation (0.7%) compared to the whole United States, Florida, and other counties (see: Fig. 2). In the United States, about 91% of households have an available vehicle and 2.8% of people walks to their workplace. In Florida, the higher percentage of household have an available vehicle (93.1%) and the lower percentage of people choose walking for commute (1.5%). Thus, Seminole County is an appropriate study area to investigate the SIN effects of an area with a small number of pedestrians.

The rest of the paper is organized as follows. The data collection section describes the process of data collection, processing, and descriptive statistics, the methodology section briefly introduces the modeling approach, and modeling results and discussions are followed. Lastly, summary and conclusions are provided.

2. Data collection

The descriptive statistics of the collected and processed data are summarized in Table 2. The data were collected from 219 intersections in Seminole County in Central Florida, United States. Crash data of 2014–2017 (four years) were acquired from the Signal Four Analytics archived by the University of Florida GeoPlan Center. During the study period, 63 pedestrian crashes occurred at the intersections.

Pedestrian and traffic data of 2017 were collected from the Automated Traffic Signal Performance Measures (ATSPM) system of Seminole County. The ATSPM is promoted by the Federal Highway Administration as a mean to enhance the traditional retiming process by providing continuous performance monitoring capability (FHWA, 2017). Two pedestrian related data were collected from the ATSPM: “Pedestrian Calls” and “Pedestrian Logs”. In urban areas with high pedestrian activity, the signal controller will be configured with a “pedestrian recall” to activate pedestrian phase every cycle. However, in rural or suburban areas with low pedestrian activity, signals are equipped with pedestrian button to “call” the pedestrian phase. The “Pedestrian Calls” means the number of “calls” for a pedestrian phase registered to the signal controller. Typically, when a pedestrian hit the call button, a “call” is registered. Different from the “Pedestrian Calls”, the “Pedestrian Logs” means the number of actual pedestrian phases activated. It means if there is a pedestrian recall, the “Pedestrian Logs” will remain in a high level without considering actual pedestrian activity (Wetzel, 2016). Two variables were calculated from those two pedestrian related data: average daily pedestrian phases requested (ADPR) and average pedestrian phases provided (ADPP), respectively. As seen in the descriptive statistics, there is no significance difference between the ADPR and the ADPP, which shows the pedestrian phases

Table 2
Descriptive Statistics.

Continuous variables	Mean	Std Dev	Min	Max
Pedestrian crashes (total 63 crashes)	0.288	0.732	0.000	7.000
Average daily pedestrian phases requested (ADPR)	41.372	39.923	4.844	240.832
Average daily pedestrian phases provided (ADPP)	44.490	40.995	5.830	243.964
Average daily traffic volume (ADT)	53888	34627	2131	183155
Proportion of residential land-use within a half mile radius	0.338	0.153	0.008	0.699
Proportion of commercial land-use within a half mile radius	0.183	0.131	0.000	0.606
Proportion of industrial land-use within a half mile radius	0.030	0.053	0.000	0.331
Proportion of institutional land-use within a half mile radius	0.025	0.031	0.000	0.165
Proportion of governmental land-use within a half mile radius	0.053	0.049	0.000	0.328
Proportion of agricultural land-use within a half mile radius	0.016	0.035	0.000	0.206
Proportion of school land-use within a half mile radius	0.021	0.035	0.000	0.189

Categorical variables	Category	Frequency	Percent
Number of legs	3	35	15.98%
	4	184	84.02%
Number of pedestrian crosswalks	1	12	5.48%
	2	52	23.74%
	3	48	21.92%
	4	107	48.86%
Skewed intersection	Yes	56	25.57%
	No	163	74.43%
Curved intersection	Yes	102	46.58%
	No	117	53.42%
Located at an interchange ramp	Yes	11	5.02%
	No	208	94.98%
Speed limit category of the major approach	55-64 mph	2	0.91%
	41-54 mph	152	69.41%
	31-40 mph	53	24.20%
	21-30 mph	12	5.48%
Speed limit category of the minor approach	41-54 mph	11	5.02%
	31-40 mph	36	16.44%
	21-30 mph	134	61.19%
	6-20 mph	32	14.61%
	Less than 6 mph	6	2.74%
Whether the speed limit categories of major and minor approaches are same	Yes	24	10.96%
	No	195	89.04%

Table 3
Bayesian random-parameter Poisson-lognormal model for pedestrian crashes.

Variable	Mean	S.D.	Bayesian Credible Interval			
			2.5%	5.0%	95.0%	97.5%
Intercept	−9.849**	1.211	−13.130	−12.510	−8.048	−7.377
random parameter: s.d. of intercept	0.234**	0.211	0.027	0.033	0.685	0.788
Log of average daily pedestrian phases provided (ADPP)	1.014**	0.221	0.585	0.630	1.346	1.413
random parameter: s.d. of average daily pedestrian phases provided (ADPP)	0.092**	0.052	0.025	0.029	0.192	0.216
Log of daily average traffic volume (ADT)	0.310**	0.130	0.028	0.090	0.531	0.577
Number of pedestrian crosswalks	0.408**	0.220	−0.004	0.056	0.774	0.852
Whether the speed limit categories of major and minor approaches are same	−0.867*	0.599	−2.118	−1.900	0.057	0.201
Curved intersection	−0.767**	0.328	−1.425	−1.316	−0.238	−0.128
Located at an interchange ramp	1.230**	0.705	−0.236	0.045	2.318	2.543
s.d. of θ	0.250**	0.228	0.027	0.033	0.726	0.849
DIC	255.357					
R^2	0.558					

** credible at 95% level, and * credible at 90% level.

are provided upon requested in the study area. In this study, ADPP was used as an exposure for pedestrian trips because ADPP might have more information about the historical pedestrian activities. Average daily traffic volume of the intersections in this study is total entering vehicles, which was also collected from ATSPM.

Land-use data of 2017 were acquired from the Florida Department of Revenue. The proportion of each land-use type within a half mile radius from the center points of the intersections was calculated and attempted in the crash model. Residential land-use has the largest proportion (33.8%) and commercial land-use follows (18.3%). Governmental and industrial land-uses are 5.3% and 3%, respectively. In addition, institutional, school, and agriculture land-uses are less than 5%.

Geometric design characteristics of intersections were manually collected from Google Earth and Google Street View (e.g., legs, pedestrian crosswalks, skew angle, curve, ramp). The majority of the intersections have four legs (84.0%), and about half of the intersections have four pedestrian crosswalks. Skewed intersections (defined as skew angle less than 10 °) are about 74% and curved intersections are slightly less than half (46.6%). Approximately 5% of intersections are located at interchanges.

Speed limit data were collected from NAVTEQ (provided by the Florida Department of Transportation). The majority of speed limit of the major approach is 41–54 mph (69.4%) while the majority of speed limit of the minor approach is 21–30 mph (61.2%). An additional variable was created using the two speed limit variables, which is whether the speed limit categories of major and minor approaches are the same. It was shown that about 11% of intersections have the same speed limit categories of major and minor approaches.

3. Methodology

This study employed a Bayesian random-parameter Poisson-lognormal model to explore the SIN effects in the study area. Poisson-lognormal models have been used as an alternative to Poisson models to account for the over-dispersed crash data (Abdel-Aty et al., 2013; Wang and Kockelman, 2013; Lee et al., 2014a, b; Lee et al., 2015a, b; Dong et al., 2016; Cai et al., 2017, 2018). A Poisson-lognormal model is specified as follows:

$$y_i \tilde{} Poisson(\lambda_i) \tag{2}$$

$$\lambda_i = \exp(\beta X_i + \theta_i) \tag{3}$$

$$\theta_i \tilde{} Normal(0, 1/\tau_\theta) \tag{4}$$

where X_i is a vector of independent variables, β is a vector of parameters to be estimated, θ_i = error component of the model, and τ_θ = precision parameter (inverse of the variance), which follows a prior gamma (0.001, 0.001). The variance, $1/\tau_\theta$, provides the amount of variations that is not explained by the Poisson assumption (Lawson et al., 2003).

In order to account for heterogeneity across observations, random parameters were estimated for intercept and the log of the average daily pedestrian phases provided (ADPP). The random parameters are formulated as follows (Gkritza and Mannering, 2008; Milton et al., 2008; Anastasopoulos and Mannering, 2009; Alarifi et al., 2017; Cai et al., 2018):

$$\beta_i = \beta + \varphi_i \tag{5}$$

where β is the mean parameter estimate across all observations and φ_i is a random distribution term following $Normal(0, \sigma^2)$, which captures unobserved heterogeneity across observations. Please note that β_i is specific for each intersection.

The model was run considering informative normal priors for β s using MCMC (Markov Chain Monte Carlo) method. The informative priors were obtained from the preliminary non-Bayesian negative binomial models that were estimated by maximum likelihood estimation (Yu and Abdel-Aty, 2013). The significance of the parameters was determined based on Bayesian confidence interval (BCI). The BCI infers on the true parameter value. For example, a 95% BCI contains the true parameter value with approximately 95% certainty.

The final model was chosen based on deviance information criterion (DIC) as follows (Spiegelhalter et al., 2002):

$$DIC = 2 \times \bar{D} - \hat{D} \tag{6}$$

where, $\bar{D}$ is the posterior mean of deviance D, $\hat{D} = 2 \times p(y|\bar{\theta})$, and $\bar{\theta}$ is the posterior mean of θ.

4. Modeling results

Table 3 presents the modeling results. The final model was chosen based on the value of DIC (255.357) and its R^2 was 0.558 that indicates the model performance is acceptable. 'Log of average daily pedestrian phases provided (ADPP)' has a positive association with the number of pedestrian crashes, with 95% Bayesian credible interval. The variable led to a random parameter with a mean of 1.014 and a standard deviation of 0.092. It indicates that the SIN effects vary from intersection to intersection. More detailed discussions on the SIN effects are provided in the discussion. 'Log of daily average traffic volume (ADT)' was found credible at 95% and has a positive effect, as expected. In addition, 'Number of pedestrian crosswalks' and 'Located at an interchange ramp' are positively associated with the number of pedestrian crashes. On the other hand, 'Whether the speed limit categories of major and minor approaches are same' and 'Curved intersection' are negatively associated with the number of pedestrian crashes. None of land-use variables were included as they are either highly correlated with the

Table 4
Chi-square test with contingency table.

Classification	ADPP Range	No SIN	SIN	Sum	Percentage of the intersections with no SIN effect
High pedestrian volumes (> 75 percentile)	ADPP > 60.31	37	18	55	67%
Medium pedestrian volumes (Between 75 percentile and 25 percentile)	16.91 < ADPP ≤ 60.31	96	13	109	88%
Low pedestrian volumes (≤ 25 percentile)	ADPP ≤ 16.91	54	1	55	98%
Sum		187	32	219	85%

$\chi^2 = 2.311$ ($p < .0001$).

ADPP or insignificant.

5. Discussion of potential for the safety-in-numbers

Since the coefficient of 'Log of ADPP' was a random parameter, the coefficient for each intersection was obtained from the modeling result. If the coefficient of ADPP is one or greater at an intersection, the intersection does not show the SIN effect. On the other hand, if the coefficient is smaller than one, we can determine that the SIN effect was observed at the intersection. As shown in the modeling results, the SIN effect for pedestrian safety was not observed in all intersections in the study area. Out of 219 intersections, only 32 intersections had the SIN while 187 did not. We made an assumption that the SIN effects are not shown because the pedestrian activities in the study area are very low. We conducted two statistical tests to prove the assumption: *t*-test and Chi-square test with contingency table. The *t*-test compared the numbers of ADPP between the two types of intersections (No SIN vs. SIN). The test indicates that the mean ADPP of the intersections without the SIN effect (37.781) is significantly smaller than that of the intersections with the SIN effect (83.701), as t-statistics is -4.849 ($p < 0.001$).

From the previous *t*-test, we found that the intersections with the SIN effect tend to have higher pedestrian volumes while those without SIN are likely to have lower pedestrian volumes. We further conducted a Chi-square test with contingency table to confirm the finding. Intersections in the study area have been classified into three groups based on their pedestrian volumes. The SIN effect by the intersection classification was summarized in the contingency table and the Chi-square value was presented accordingly (Table 4).

The Chi-square test showed that the proportions of the SIN effects are significantly different by the classification. Among the intersections with high pedestrian volumes, 67% of them did not show the SIN effects. The percentage of the intersections with non-SIN effects is higher at those with medium pedestrian volumes, 88% (97/109). Furthermore, among those low pedestrian volumes, the percentage of non-SIN effect intersections is 98% (54/55).

From these results, it could be concluded that it is not always true that intersections with high pedestrian activities have the SIN; but there is a tendency that intersections with lower pedestrian activities do not have the SIN effects, in most of the cases.

6. Conclusions

The safety-in-numbers is a phenomenon that when the number of pedestrians or bicyclists increases, their risk (or crash rate) decreases. In other words, pedestrians or bicyclists would be safer from traffic crashes if their number increases as drivers would be more cautious for them. The SIN effects for active modes of transportation have been confirmed by many previous studies. In this study, we focused on the SIN effects for pedestrians in areas with a low population density and low pedestrian activities. We collected data from a suburban county of Central Florida of the United States. A Bayesian random-parameter Poisson-lognormal model was estimated to account for the possible different SIN effects across the intersections. One of the advantages of the random-parameter modeling is that it uses all observations to estimate a coefficient and can account for unobserved heterogeneity across observations, simultaneously. The modeling results revealed that the natural logarithm of pedestrian activities led to a random parameter with a mean of 1.014 and a standard deviation of 0.092, which shows that the SIN effects vary from intersection to intersection. It was shown that only 32 intersections among 219 had the SIN effects. The intersections with the SIN have relatively larger pedestrian activities whereas those without the SIN have very low pedestrian activities, which were confirmed by the *t*-test and Chi-square tests.

The findings from this study have an important policy implication that just aiming to encourage people to walk in regions with an extremely low pedestrian activities cannot reduce the pedestrian safety risk until the pedestrian activities increase to a sufficient level. In order to increase the pedestrian activities without exposing pedestrian to high crash risk, it is essential to provide safe walking environments for them. Proven pedestrian safety countermeasures include but not limited to (1) providing sidewalks and paved shoulders (Bahar et al., 2008), which could reduce pedestrian crashes by 65–89% and 71%, respectively; (2) leading pedestrian interval at crosswalks that provides pedestrian the chances to enter an intersections 3–7 s earlier than vehicles are given a green signal (Fayish and Gross, 2010), which is able to reduce pedestrian crashes by 60%; (3) installing raised median and pedestrian crossing island (Bahar et al., 2008), which could lead to 46% and 56% reductions in pedestrian crashes, respectively; and (4) pedestrian hybrid beacons (Fitzpatrick and Park, 2010) is proven effective to reduce pedestrian crashes by 69%. In addition, implementing complete streets, which is a people-oriented transportation systems policy, will be effective to make walking environments safer (LaPlante and McCann, 2008). After safe walking environments are guaranteed and when people recognize that walking is safe, more people will consider walking for short-distance trips. Eventually, increased pedestrian activities will result in the SIN effects and walking will be even further safer.

Although this study revealed important findings, it is not without limitation. First, the current study relies on ADPP (average pedestrian phases provided). Although ADPP is a useful surrogate exposure for pedestrian trips, it cannot capture the actual number of pedestrian trips. Especially when there is a high variation in the number of pedestrians crossing in different intersections, it might lead to a biased result. Second, several geometric and traffic factors are taken into account in the model; but other socio-economic and environmental factors are not considered (e.g., industry, income, climate, weather, air quality). Lastly, the current study focused solely on intersections. It might be more useful for policy-makers if the similar study is performed for more macroscopic level (e.g., county, city). These limitations should be considered and overcome in the follow-up studies.

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