https://doi.org/10.1016/j.jsr.2021.02.008

Investigating the uniqueness of crash injury severity in freeway tunnels: a comparative study in Guizhou, China

Zhou Zichu[1], Meng Fanyu[2,*], Song Cancan[1], Sze N. N.[3], Guo Zhongyin[1], Ouyang Nan[4]

[1] *Key Laboratory of Road and Traffic Engineering of the Ministry of Education, Tongji University, Shanghai, China*

[2] *Academy for Advanced Interdisciplinary Studies, Southern University of Science and Technology, Shenzhen, China*

[3] *Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong, China*

[4] *Guizhou Transportation Planning Survey & Design Co., Ltd, Guiyang, China*

[*] corresponding author. Email: mengfy@sustech.edu.cn. Address: 1088 Xueyuan Ave, Shenzhen 518055, China.

Investigating the uniqueness of crash injury severity in freeway tunnels: a comparative study in Guizhou, China

Abstract:

With the rapid development of transportation infrastructures in precipitous areas, the mileage of freeway tunnels in China has been mounting during the past decade. Provided the semi-constrained space and the monotonous driving environment of freeway tunnels, safety concerns still remain. This study aims to investigate the uniqueness of the relationships between crash severity in freeway tunnels and various contributory factors. The information of 10,081 crashes in the entire freeway network of Guizhou Province, China in 2018 is adopted, from which a subset of 591 crashes in tunnels is extracted. To address spatial variations across various road segments, a two-level binary logistic approach is applied to model crash severity in freeway tunnels. A similar model is also established for crash severity on general freeways as a benchmark. The uniqueness of crash severity in tunnels mainly includes three aspects: (1) the road-segment-level effects are quantifiable with the environmental factors for crash severity in tunnels, but only exist in the random effects for general freeways; (2) tunnel has a significantly higher propensity to cause severe injury in a crash than other locations of a freeway; and (3) different influential factors and levels of contributions are found to crash severity in tunnels compared with on general freeways. Factors including speed limit, tunnel length, truck involvement, rear-end crash, rainy and foggy weather and sequential crash have positive contributions to crash severity in freeway tunnels. Policy implications for traffic control and management are advised to improve traffic safety level in freeway tunnels.

Keywords: crash injury severity; freeway tunnel; multilevel model; unobserved heterogeneity; road safety

1. Introduction

With the growing need of transport connectivity of modern transportation network, transport developments in precipitous areas, such as mountains, waters and valleys, has become utterly necessary and popular. Owing to the advancement in road designing and construction capabilities, infrastructures such as tunnels and bridges have been widely utilized to fulfill the requirements of massive highway network development, in which road tunnels play a crucial part. In China, the total number of highway tunnels has reached 17,738, with the total mileage passing 17,000 km (Ministry of Transport, 2019). The boosting number and total mileage has brought the difficulties of tunnel maintenance and tunnel traffic organization to a higher level.

Safety concerns of highway tunnels have always been puzzling researchers and practitioners in the past few years. Unlike driving on an open road, driving in a highway tunnel has more hidden hazards by nature. Firstly, visual adaptation to different lighting conditions inside and outside a tunnel has been proved to be hazardous. The entrance and the exit, where the adaptations exist, have been proved to hinder the driver from proper visual processing and thus induces higher crash risks (Mehri et al., 2019). Besides, driving within a tunnel may generate anxiety since the environment is rather constrained, dark and monotonous (Caliendo & De Guglielmo, 2012; Ma et al., 2009). While driving in a tunnel, a driver needs to keep in mind with all the restrains such as the speed limit, the restraint on lane changing, the distance to the tunnel wall, etc. Nerves originating from the special driving environment is possible to distract the drivers from identifying risks from the traffic, and may cause fatigued driving behaviors (Meng et al., 2019). Moreover, combinations between the unique driving environment and other factors, such as road alignment, traffic and weather, may also give way to a severe road accident in a tunnel. For example, due to terrain restrains, freeways in mountainous and plateaued areas are commonly designed with more curves, higher slopes and longer downhills compared to freeways on the plains (Huang et al., 2018). Intercity highways and freeways with active cargo transportation can lead to higher percentage of heavy trucks, which may then result in visual problems to the rear car (Das et al., 2020; Jo et al., 2019). Extreme weathers such as rain, snow and fog can also give rise to more severe and fatal injuries based on multiple previous studies (Ma et al., 2019; Meng et al., 2017; Sun et al., 2018). The existing hazards of the abovementioned characteristics can only aggravate the risk level of road tunnels.

In addition to the hazardous and complicated driving environment, the consequences of an accident occurring in a tunnel tend to be more destructive and catastrophic than an accident on an open road, as the narrower and more constrained space in a tunnel hampers the post-accident proposal and evacuation, which may cause a slowdown or a breakdown of the transport system and may also give rise to subsequent crashes (Amundsen & Ranes, 2000; Huang et al., 2018; Yeung et al., 2013). If a fire is caused in the tunnel, the narrow and enclosed space may also slow down the dissipation process of heat and smoke (Ma, et al., 2009). Complications in post-accident management emphasizes the importance of understanding factors imposing severe tunnel traffic accidents and implementing effective precautions for them.

Given the existence of potential hazards in a road tunnel, studies regarding driving behaviors in tunnels have been carried out, mostly using a driving simulator, and the effects of different tunnel wall patterns, lighting conditions and information reminders have been proved significant to affect driving behaviors in tunnels (He et al., 2010; Hirata et al., 2006; Shimojo et al., 1995; Törnros, 2000). Regarding road tunnel safety, much effort has been endeavored to predicting crash frequencies, where significant factors associated with high crash risks have been identified with possible unobserved heterogeneities and spatial/temporal effects addressed (Caliendo & De Guglielmo, 2012; Caliendo et al., 2013; Caliendo et al., 2019; Hou et al., 2018; Meng & Qu, 2012; Yeung & Wong, 2013). However, few studies have established models on the crash severity in road tunnels, especially in freeway tunnels. Ma et al. (2016) adopted a generalized ordered logit modeling approach to investigate contributive factors associating with crash severity of 134 crashes in four specific freeway tunnels occurring in a two-year period of time. Factors including time of day, location of crash, tunnel length and weather were proved contributive to freeway tunnel crash severity. Huang et al. (2018) employed a classification and regression tree model to identify risk factors associating with injury severity of crashes on a 61-kilometer-long freeway segment with continuous twelve one-way two-tube tunnels, and concluded that factors such as unsafe driving behaviors, crash time, grade and vehicle types significantly affected the crash severity.

Although several studies have shed light on possible influential factors for freeway tunnel crash injury severity, there are still obvious limitations in two dimensions. First, the exiting studies failed to analyze freeway tunnel crash severities with a comparative perspective. A thorough comparison between crash severities for freeway in general and specifically for freeway tunnels should be conducted to unmask the uniqueness of freeway tunnel crashes. Second, unobserved heterogeneities, as commonly addressed while modeling crash frequency and severity (Aldred et al, 2019; Anastasopoulos & Mannering, 2009; Chen, et al., 2019; Mannering & Bhat, 2014; Mannering et al., 2016; Xu et al., 2019), haven't been tested in previous studies on crash severity in freeway tunnels. Provided that most crash datasets are hierarchical in which some hyperparameters (i.e., traffic-site-level factors) may have spatially different effects on crash severity, because facility qualities and enforcement levels may vary across traffic sites (Huang and Abdel-Aty, 2010; Dupont et al., 2013). Besides, it is nearly impossible for empirical datasets to incorporate all contributive spatial factors associating with crash severity. Hence, spatial heterogeneities (cross-group variations) may still exist and cause biased results if not properly addressed (Besharati et al., 2020; Meng et al., 2017; Venkataraman et al., 2011).

The current study aims to investigate the relationships between influential factors and crash severity in freeway tunnels of Guizhou province, China. As a typical mountainous province, Guizhou has raised its number of freeway tunnels to 1,433, and the kilometrage has reached 1,493, nearly double of the same numbers in year 2016 (Guizhou Traffic Information and Emergency Control Center, 2018). A two-level binary logistic regression model is established to quantify the relationships between crash severities in freeway tunnels and contributory factors based on police-recorded crashes in 2018, in which hierarchical spatial effects are addressed. The same approach is also applied to general freeways in Guizhou province, as a benchmark for its tunnel counterparts. Significant factors influencing tunnel crash severity are identified, and policy implications are made to improve further safety management in freeway tunnels.

2. Data

A crash database provided by Guizhou Traffic Information and Emergency Control Center (affiliated to Department of Transportation of Guizhou Province) is applied. The data were originally recorded and managed by onsite traffic police teams who proposed all incidents taking place in the freeway network. The database recorded crash information of freeways in Guizhou Province covering all crashes occurring on the total of 6,390 km of national, provincial and local freeways in the province in 2018. The percentage of tunnel lengths in the freeway network was 23.1% (1,493 km). To facilitate freeway management, the whole network is further divided into 75 road segments, and the average length 85.2 km. A total of 10,081 crashes on the freeways were recorded in 2018 and 591 of them happened in a tunnel, covering 45 road segments and 343 tunnels. Crash-level characteristics including crash type, number of vehicles involved, vehicle involvement, fatality and injury are recorded for each crash. Among all crashes in 2018, 8,903 are crashes with property damages only (PDO) and 115 are fatal crashes (with no less than one death within 7 days), and the rest causes as least one injury per crash (without fatality). In this study, the crashes were classified into two severity categories: non-severe crashes (PDO crashes) and severe crashes (fatal crashes and crashes with injuries).

To facilitate a multilevel modeling scheme, predictors are classified as crash characteristics (level 1 variables) and environmental factors (level 2 variables) as shown in Table 1. Crash-level attributes include crash types, involvement of various types of vehicles, number of involved vehicles and sequential crash. The type of vehicles involved in each crash was logged based on the vehicle type categorization scheme designed to differentiate levels of toll fees for various vehicle types. All vehicles are divided to two main categories majorly based on the function: passenger vehicle and cargo vehicle. Passenger vehicles are further classified into small passenger vehicles, mini-buses and buses, according to their different sizes and numbers of seats. Cargo vehicles are categorized based on the size and weight into mini-truck, truck, and trailer truck. In this study, crashes with trailer trucks, buses and trucks involved are the mainly studied vehicle involvement types. As these types of vehicles are heavy and large in sizes, it is relatively easier to lose control at a high speed, and more difficult for the drivers to properly control the vehicle to evade from an emergency situation.

Environmental information of each crash, such as date, time, location and weather, is also extracted from the database. Based on previous research on road safety, six representative time periods within a day are defined in this study: dawn (3 a.m. to 7 a.m.), morning (7 a.m. to 11 a.m.), noon (11 a.m. to 3 p.m.), afternoon (3 p.m. to 7 p.m.), evening (7 p.m. to 11 p.m.) and night (11 p.m. to 3 a.m. of the next day) (Pei et al., 2012). Adverse weather was proved to be more likely to cause severity injuries in tunnels (Ma, et al., 2016), and thus in this study, typical adverse weather conditions including rainy, cloudy, foggy and frozen were defined.

Road design information such as speed limit (80/100/120 km/h according to regulations of Chinese freeways) and number of lanes (two/three lanes for uni-direction freeways) at each crash point are also classified as upper-level attributes, as they are usually identical for the entire road segment. Besides, if a crash took place in a tunnel, the length of the tunnel is also collected. According to the designing codes of highway tunnels in China, highway tunnels are categorized into four types based on its length: super-long tunnel (longer than 3000 m), long tunnel (1000 m to 3000 m), middle-long tunnel (500 m to 1000 m) and short tunnel (shorter than 500m), and different designing standards apply to different categories (Ministry of Transport, 2004). In 2018, crashes occurred in 328 tunnels in Guizhou freeways, and the average length of these tunnels is 1,428m. Among these tunnels, 33 were super-long tunnels, and the maximum length of them were 4,755 m (Zhaoxing Tunnel). Previous studies have found that both crash risk and injury severity in tunnels tend to increase with tunnel length. Besides, only 11 crashes occurred in short tunnels among all 591 tunnel crashes in our database. Hence, short and medium tunnels were further combined as “others” and used as the baseline category, and the focus is gathered on the effects of relatively longer tunnels (i.e., the riskier ones proven by previous studies).

The descriptive statistics of the variables incorporated in the models are displayed in Table 1. For the continuous variable (speed limit), the minimum and maximum values, and mean values and standard deviations (SDs) are provided; categorical variables were transformed to dummy variables, and the percentage of each category among all observations were provided.

Table 1. Descriptive statistics of dependent and independent variables

Variable name	Category/ explanation	General freeway model (GFM)		Tunnel model (TM)	
		Mean/ Percentage	SD	Mean/ Percentage	SD
Depend variable:					
Crash severity	Severe	11.7%		27.9%	
	Non-severe (base)	88.3%		72.1%	
Crash characteristics:					
Truck involvement	Truck involved	26.9%		29.3%	
	No Truck involved (base)	73.1%		71.7%	
Trailer truck involvement	Trailer truck involved	7.1%		6.6%	
	No trailer truck involved (base)	92.9%		93.4%	
Bus involvement	Bus involved	1.1%		1.5%	
	No bus involved (base)	98.9%		98.5%	
Crash type	Rear-end	36.7%		57.4%	
	Flip-over	6.1%		5.2%	
	Side-swipe	4.8%		1.7%	
	Hitting fixtures (base)	52.4%		35.7%	
Number of vehicles	Single-vehicle	58.2%		48.6%	
	Multi-vehicle (base)	41.8%		51.4%	
Sequential crash	Crash belonging to a crash sequence	5.9%		19.6%	
	Crash belonging to no crash sequence (base)	94.1%		80.4%	
Environmental factors:					
Speed limit	In: km/h	115.8	11.34	89.1	16.8
Time period	Dawn (3:00-7:00)	5.8%		3.2%	
	Morning (7:00-11:00)	17.0%		15.9%	
	Noon	24.9%		36.2%	

	(11:00-15:00, base)				
	Afternoon (15:00-19:00)	25.5%		27.9%	
	Evening (19:00-23:00)	18.0%		10.0%	
	Night (23:00-3:00)	8.8%		6.8%	
Location	Tunnel	5.8%		-	-
	Ramp	4.4%		-	-
	Bridge	0.5%		-	-
	Open road (base)	94.2%		-	-
Number of lanes	Two-lane (base)	87.6%		100%	
	Three-lane	12.4%		0%	
Weather	Rainy	19.4%		15.6%	
	Cloudy	62.2%		62.6%	
	Foggy	0.5%		1.0%	
	frozen	1.4%		0.7%	
	Sunny (base)	16.5%		20.1%	
Tunnel length	Super-long tunnel	-	-	49.1%	
	Long tunnel	-	-	24.4%	
	Short and medium tunnel (base)	-	-	26.6%	

3. Method

3.1. Two-level binary logistic model

To quantify the relationships between explanatory variables and various severity levels, a logistic function has been widely used in previous studies (Celik & Oktay, 2014; Huang et al., 2016; Shaheed et al., 2016; Wu et al., 2014). To avoid biased estimations cause by within-road-segment correlation, the spatial heterogeneity varying across road segments is address by a two-level modeling scheme (Huang and Abdel-Aty, 2008). On the crash level (level 1), the outcome variable representing the severity levels of each crash has two categories: severe and non-severe. Hence, denote Y_{ij} as the severity of crash i on road segment j. $Y_{ij} = 1$ means that the crash i is severe, and $Y_{ij} = 0$ means that the crash i is non-severe. A binary logistic function is able to link the probability of $Y_{ij} = 1$ (denoted as p_{ij}) with the crash-level independent variables as follows (McFadden, 1973):

, (1)

where X_{ijk} is the value of the kth level 1 independent variable for crash i on road segment j, is the crash-level intercept, is the estimated coefficient for X_{ijk}, and e_{ij} is the random error term following a logistic distribution.

To account for the cross-crash variations, the road-segment-level (level 2) model is specified as:

, (2)

, (3)

where and are estimated intercepts on the road segment level; is th level 2 independent variable representing environmental factors for road segment , and is the estimated coefficient for ; and are the random effects varying across road segments for the crash-level intercept and crash-level covariate with means zero and variances and , respectively (Snijders and Bokser, 2000). Note that the random effects, and , are random across road segments and constant for all crashes on the same road segment, which enables unobservable spatial effects varying between road segments (Kim et al., 2007).

A simulated maximum likelihood estimation method with 200 Halton draws is applied to estimate the coefficients (McFadden, 1973; Train, 2009). A Z test was applied to each estimated coefficient to acquire the statistical significance level.

3.2. Elasticity analysis

An elasticity analysis is extensively considered necessary for understanding the effect of each independent variable on the dependent variable (Kim et. al., 2013; Wu et al., 2014, Li et al., 2019). The elasticity for a continuous independent variable on the probability of a severe crash is calculated from t partial derivative of each observations (Washington et al. 2020):

(4)

where the is the elasticity outcome for continuous variable of crash observation in road segment . As the probability for a crash to be severe is not differentiable with dummy independent variables, a pseudo-elasticity is defined for indicators as follows (Kim et al., 2007):

(5)

where is the pseudo elasticity of dummy variable of crash observation in road segment . The final elasticity of a variable is calculated as the sample mean of the elasticity outcomes for all observations.

4. Results

Based on the two-level binary logistic modeling scheme, two crash severity models were established: the model for general freeways (GFM) and the model for freeway tunnels (TM). The GFM contained the crashes occurring on the whole freeway network of Guizhou province in the observation period, with all road segments and infrastructures (i.e., open-road, bridge, tunnel and ramp) included. The TM included only the crashes occurring in the tunnels of the same freeway network. As crash injury severity on general freeways have been investigated thoroughly from various aspects, the GFM in this study serves as a benchmark, and the comparison between the TM and the GFM provide insights of the mechanism and the uniqueness of crash severity in freeway tunnels.

Before performing the regression, Pearson correlation between each pair of the independent variables was calculated, and all the Pearson correlation value were smaller than 0.6, meaning that there is no significant correlation between independent variables in this study. As illustrated in “Data”, the full dataset displayed in Table 1 was adopted to estimate the GFM, and its subset of tunnel crashes was used to estimate the coefficients in the TM. Certain differences existed in the choices of independent variables in the two models. Firstly, as the GFM covered crashes taking place in the whole freeway network, the location effect (i.e., tunnel, bridge, ramp and others) was assumed to contribute to general freeway crash severity (see Table 1). Secondly, tunnel length was adopted in the TM to quantify the effects of super-long, long and short tunnels to crash severity in tunnels. Thirdly, as all observations in tunnels in this case took place in two-lane tunnels, “number of lanes” had to be excluded from the TM. Besides, the unique variable, “tunnel length”, were interacted with the involvement of various types of vehicles and “crash type”, respectively, and incorporated in the TM. As drivers’ adaptation abilities to hazardous driving environment may vary, the effect of tunnel length (especially in long and super-long tunnels) on driving safety has been ambiguous in previous studies (Caliendo et al., 2013). Hence, interactions between tunnel length and crash-level attributes is assumed to unveil this complicated nature. The interaction terms with insignificant coefficient at the 95% confidence level or above were excluded from the final model, and only the ones with significant coefficients were kept.

At first, all variables on both levels are incorporated according to the two-level settings stated in “Methods”. For environmental effects (level 2 variables), if the fixed coefficients of all its sub-categories are insignificant, the variable is assumed to have no significant effect on the dependent variable and thus excluded from the modeling. For the crash characteristics (level 1 variables), insignificant random effects are assumed to have weak associations with the dependent variable and removed from the modeling. For categorical variables on both levels, the estimates for the dummy variables of all categories are kept if at least one category is significant at the 95% confidence level, to keep the consistency for variable definition and facilitate comparison between models. Final estimation and elasticity results were listed in Table 2 and Table 3, for the GFM and TM, respectively.

In the GFM (see Table 2), 8 fixed effects were significant at the 0.05 level or above including the intercept, . Among all crash-level variables with a significant fixed coefficient, 1 variable (sequential crash) had a significant random slope. The random intercept varying across road segments was also significant at the 0.05 level. In the TM model (see Table 3), 9 fixed effects were significant at the 0.05 level or above. Among the tested interactions terms, the interaction between “rear-end” and “super-long” tunnel was significant, and thus kept in the final model. The S.D. of road-segment-level random intercept and the S.D. of “rear-end” were also significant at the 0.05 level.

Table 2. Estimation results for the crash severity model for general freeways (GFM).

Variable	**Coefficient**	**Standard error**	**P>∣Z∣**	**Elasticity**
Fixed effects:				
Intercept	-3.292***	0.168	0.000	-27.9%
Location:				
- Tunnel	1.034***	0.243	0.000	4.6%
- Ramp	1.033***	0.273	0.000	3.8%
- Bridge	1.740**	0.760	0.022	0.6%
- Open road (base)				
Truck involvement:				
- Truck involved	1.137***	0.183	0.000	24.0%
- No truck involved (base)	-	-	-	-
Trailer truck involvement:				
- Trailer truck involved	1.136***	0.263	0.000	5.4%

- No trailer truck involved (base)	-	-	-	-
Crash type:				
- Rear-end	0.045	0.186	0.808	1.5%
- Flip-over	0.688^{**}	0.257	0.007	3.3%
- Side swipe	-0.399	0.489	0.415	1.7%
- Hitting fixture (base)	-	-	-	-
Crash-chain:				
- Sequential crash	0.959^{**}	0.243	0.000	5.7%
- Non-sequential crash (base)	-	-	-	-
Random effects:				
Intercept (S.D.)	0.439^{***}	0.121	0.000	-
Sequential crash (S.D.)	1.045^{**}	0.432	0.016	-
Number of observations			10081	
Log-likelihood at convergence			-1387.439	
McFadden Pseudo			0.801	
			11200.355	
AIC			2798.9	

**: estimated coefficient significant at the 95% confidence level;

***: estimated coefficient significant at the 99% confidence level.

Table 3. Estimation results for the crash severity model for tunnels (TM).

Variable	**Coefficient**	**Standard error**	**P>$\|Z\|$**	**Elasticity**
Fixed effects:				
Intercept	-4.356^{***}	0.899	0.000	-27.8%
Speed limit	0.016^{**}	0.008	0.044	102.4%
Tunnel length:				
- Long tunnel	1.101^{***}	0.373	0.003	37.4%
- Super-long tunnel	0.601	0.538	0.264	9.9%
- Short and medium tunnel (base)	-	-	-	-
Weather:				
- Rainy	1.425^{***}	0.444	0.001	11.8%
- Cloudy	0.388	0.364	0.286	17.1%
- Foggy	4.085^{***}	1.164	0.000	1.1%
- Frozen	0.684	1.377	0.620	0.3%
- Sunny (base)	-	-	-	-
Time period:				
- Dawn	0.923	0.629	0.143	1.6%
- Morning	-0.724^{*}	0.375	0.053	-8.3%
- Afternoon	-0.713^{**}	0.339	0.036	-15.0%
- Evening	-0.719	0.479	0.134	-5.2%
- Night	-0.864	0.545	0.113	-4.3%
- Noon (base)	-	-	-	-

Truck involvement:				
- Truck involved	1.315***	0.286	0.000	21.8%
- No truck involved (base)	-	-	-	-
Crash type:				
- Rear-end	1.118***	0.424	0.008	37.2%
- Flip-over	0.587	0.533	0.271	1.9%
- Side swipe	1.349	0.922	0.144	1.1%
- Hitting fixture (base)	-	-	-	-
Crash-chain:				
- Sequential crash	0.878**	0.389	0.024	9.7%
- Non-sequential crash (base)	-	-	-	-
Interaction term:				
Rear-end ´ super-long tunnel	1.777***	0.608	0.004	-
Random effects:				
Intercept (S.D.)	0.837***	0.183	0.000	-
Rear-end (S.D.)	0.550**	0.244	0.024	-
Number of observations			591	
Log-likelihood at convergence			-240.607	
McFadden Pseudo			0.413	
			338.087	
AIC			523.2	

**: estimated coefficient significant at the 95% confidence level;

***: estimated coefficient significant at the 99% confidence level.

5. Discussion

This section aims to discuss the unique associations between tunnel crash severity and various crash and environmental characteristics. To facilitate the discussions on the uniqueness of tunnel crash severity, the significant influential factors associating with crash severity in freeway tunnels in the TM are discussed in a comparative manner, with the GFM as a benchmark.

5.1. General differences between GFM and TM

Based on the multilevel model structure, moderating effects of various road segments were proven solid in both the GFM and the TM. In the GFM, four crash-level variables were statistically significant at the 0.05 level, namely truck involvement, trailer truck involvement, rear-end crash and sequential crash, among which the higher-level random effect for sequential crash was significant (coefficient=1.045). Besides, the crash-level intercept can be expressed as a function of various locations (i.e., tunnel, ramp and bridge) of the crashes and a negative constant (coefficient=-3.292). The significant random effects in the intercept and “rear-end” crash explains the cross-road-segment variances.

In the TM, similar random effects were found significant in the intercept and “read-end”, addressing the heterogeneity across various road segments. Three crash-level factors had a significant estimated coefficient after the road-segment random effects being addressed. Unlike the results in the GFM, multiple level 2 variables were significant at the 0.05 level in the TM, including tunnel length, rainy and foggy weather and afternoon. This result indicates that compared to general freeways, the higher-level spatial effects of tunnel crash severity are rather unique, as they are quantifiable with higher-level covariates but can only be addressed by random terms for general freeway severity.

Moreover, the coefficients of “tunnel” (coefficient=1.034), “ramp” (coefficient=1.033) and “bridge” (coefficient=1.740) were significantly positive at the 0.05 level or above in the GM. Compared to open road sections, infrastructures like tunnels, ramps and bridges place potential hazards of a collision. When an emergency situation takes place, it is also more difficult for a driver to promptly react and take further actions to avoid crashes while driving inside a tunnel, on a ramp or on a bridge. The significantly positive result of “tunnel” once again proves the uniqueness of crash severity patterns in tunnels compared with general freeways and serves as a foundation of the subsequent analyses and discussions of key factors affecting severity levels of crashes in freeway tunnels.

Based on the significance levels and the estimated coefficients of the other variable in both models, the uniqueness also locates in the differences in most of the factors included in the two models. Detailed discussions on these factors are stated in the following subsections.

5.2. Tunnel length

Two variables representing different tunnel lengths where crashes happened were included in the TM (see Table 3). "Long tunnel" had a positive fixed coefficient which is significant at the 99% confidence level (coefficient=1.101). According to the elasticity analysis, a long tunnel has 37.4% higher probability to cause a severe crash than a shorter tunnel. Compare to the reference level (short and medium tunnel), a crash in a tunnel longer than 1000 m and shorter than 3000 m is more likely to cause severe or fatal injuries than the one in a shorter tunnel. Caliendo, et al. (2013) concluded that driving in long tunnels were more likely to be engaged into a collision. Ma, et al. (2016) proved that crashes in long tunnels have higher likelihood to be severe or fatal. Driving in tunnels longer than 1000 m may cause fatigued driving behaviors provided that the constraint environment and dim light might induce nerves for the drivers. Hence, a slow reaction under fatigued driving condition may cause more severe injuries in a crash.

5.3. Crash type

Rear-end crash was the only type of collision that held a significant coefficient while modeling crash severity in freeway tunnels, and the coefficient was positively significant (coefficient=1.118, elasticity=37.25%) at the 0.05 level. The result indicates that rear-end crashes in a freeway tunnel has a 37.2% higher likelihood to cause fatality or severe injury than hitting fixtures of a tunnel. Indeed, rear-end accounts for 57.4% of all crashes occurring in tunnels in our database, ranking the highest among all crash types, and this number is much higher than the percentage of rear-end crashes in total freeway crashes. Because lane changing is prohibited in Chinese tunnels, the chance for a crash from following car or to the front car is utterly much higher than other crash directions. Besides, drivers driving in a tunnel may be distracted by controlling lateral positions, e.g., controlling the lane position or keeping a distance from the tunnel wall, keeping a proper headway may be neglected to some degrees, especially for some novice drivers. Hence, the chance for an uncontrollable rear-end collision leading to severe injuries or fatalities is relatively higher.

In a tunnel longer than 3000 m, the probability for a rear-end collision to cause severe injury or fatality is rather higher. According to on modeling result for the interaction term between rear-end crash and super-long tunnel, the coefficient (1.777) was positively significant at the 99% confidence level. Rear-end crash is mainly caused by poor control of headways and slow reactions, both of which are fatigued driving behaviors (Yeung & Wong, 2014). As the effect of super-long tunnel is rather blurry, this significant effect proves that although drivers may be familiar with the tunnel environment after continuous driving in the same tunnel from longer than 3000 m, there might still be deficit in headway control and front hazard perceptions.

The estimated coefficient for "flip-over" was statistically insignificant for crash severity in freeway tunnels, but it was significant for crash severity on freeways in general (coefficient=0.688, elasticity=3.3%). For crashes on freeways, flip-over crashes have the highest likelihood to result in severe injuries or fatalities among all crash types. A possible explanation for these results is that flip-over crashes are relatively less dangerous in tunnels because the motion of flipped vehicle is protected by the tunnel structure, unlike in open area.

5.4. Sequential crash

Sequential crash is a novel definition of crash-level effect on crash severity in this study. The coefficients of this factor were significant at the 0.05 level or above and positively correlated with severity of crashes both on general freeways and in freeway tunnels. In the dataset, the percentage of sequential crashes in tunnels is nearly four times of that on the whole freeway network. Because the drivers are not allowed to change lanes in Chinese freeway tunnels, emergency braking is commonly the first reaction of the driver and the only legal method to avoid a crash in the front, which produces new hazards and spreads them to the vehicles behind in the whole lane according to the traffic wave theory (Daganzo, 1992; Richards, 1956). As the hazard of a crash spread mainly in the same lane backwards, rear-end collision chain or multi-vehicle rear-end collisions are more likely to happen in freeway tunnels, and hence results in more severe crashes.

On general freeways, a significant random effect (coefficient=1.045) is found for "sequential crash" varying across different road segments. The differences in geometric design, infrastructure quality and other environmental attributes in various road segments are possible to lead to this significant variation, as these factors are likely to affect drivers' attention and reaction speed to the motion change of the front vehicles, and thus lead to different levels of crash severity.

5.5. Vehicle involvement

Among all studied types of vehicles, truck involvement was the only one with a significant coefficient in the TM, indicating that compared to a tunnel crash with no truck, one or more involved truck tends to have a 21.8% higher possibility to cause severe injuries or fatalities (coefficient=1.315). The same factor also places a relatively higher propensity on causing a severe injury or a fatality on general freeways (coefficient=1.137, elasticity=24.0%). These results are intuitive as the massive size of a truck can block drivers from surrounding vehicles and from identifying the hazards in the traffic, and the weight of a truck (especially when filled with cargos) would incur longer braking distance and more severe injuries (Chang & Chien, 2013; Tay et al., 2011).

Trailer truck had a statistically significant coefficient while modeling crash severity on general freeways (coefficient=1.136, elasticity=5.4%), but were insignificant for crash severity in tunnels. As trailer trucks are extremely long in size, the lane changing process is cumbersome and slow, with a considerably large influential area. Since this action is prohibited in Chinese freeway tunnels, the hazardous influences are naturally eliminated.

5.6. Weather and time

In freeway tunnels, rainy and foggy days place significantly higher likelihoods on crash severity, but cloudy and frozen days has no significant difference with sunny days. Although adverse weather in general has been proven to cause more severe injuries in freeway tunnels (Ma, et al., 2016), different adverse weather conditions contribute differently to tunnel crash severity. For tunnel crashes, fog (coefficient=4.085, elasticity=1.1%) has a slightly higher possibility to incur severe injuries than sunny weather, as it is able to spread into the tunnel hole and result in worse visibility inside the tunnel (note that low visibility is already an issue resulted from poor illumination and visual adaptation problems (Mehri, et al., 2019) and may impair car-following performance (Gao et al., 2019); rain (coefficient=1.425, elasticity=11.8%) is able to wet the types of vehicles or go downgrade into the tunnel, and thus lower the friction and result in severe injuries inside tunnels (Ma, et al., 2009). It is worth noting that frozen weather is considered an extreme weather in southern China, when temperature drastically drops below 0 degree Celsius and a thin layer of ice may randomly distribute in the top layer of the pavement. This adverse weather is not significantly associated with tunnel crash severity, possibly because prohibition of lane changing in tunnels considerably reduce potential risks of misbehaviors of the vehicles because of the slippery pavement in frozen weather.

In the TM, the only significant time-of-day effect was "afternoon" (coefficient=-0.713), holding a 15.0% lower probability to cause severe injuries or fatalities in a tunnel crash than a crash occurring at noon. This possibly results from the differences in driving fatigue levels of the drivers at noon and in the afternoon. Most drivers take a short break at lunch time, and thus could refresh from fatigued driving in the afternoon.

5.7. Speed limit

The coefficient estimation for speed limit was positively significant while modeling crash severity in tunnels at the 0.05 level (coefficient=0.016, elasticity=102.4%), but it had no significant contribution to severity of crashes on general freeway. One possible reason for the different levels of effect of speed limit on crash severity in the two studied contexts is that the monotonous driving environment in tunnels tend to cause more fatigued driving behaviors, thus lead to more frequent and aggressive speeding violations. As speeding has been found to be positively correlated with injury severity on freeways (Abegaz, et al., 2014; Huang et al., 2018), speed limit is more effective in controlling speed limit in tunnels than general freeways, and consequently has relatively more significant effect on the crash severity in freeway tunnels.

6. Conclusion

This study investigated the unique relationships between crash severity in freeway tunnels and various influential factors. The information of crashes of 10,081 crashes on Guizhou freeway network in 2018 was incorporated, in which 591 crashes took place in tunnels. A two-level binary logistic modeling approach was adopted to identify significant influential factors with tunnel crash safety while addressing the road-segment-level spatial effects across observations. The similar approach was adopted for crash severity on freeway in general as a benchmark. The uniqueness of crash severity patterns in freeway tunnels mainly located in: (1) the quantifiable environmental effects, (2) the significantly higher general levels of crash severity and (3) the different levels of the effects of influential factors on crash severity compared to general freeways. Factors including speed limit, tunnel length, truck involvement, rear-end crash, rainy and foggy weather and sequential crash were found to be positively associated with crash severity in freeway tunnels. Rear-end crash was also proven to have interactive effects with super-long tunnel on tunnel crash severity.

Policy suggestions can be implied to improve driving safety in freeway tunnels based on the results in this study. For example, dynamic warning signs should be placed in and outside a tunnel (especially a long tunnel) in adverse weathers such as rainy days and foggy days. Similar measures can be implemented in long and super-long tunnels reminding the drivers to keep a decent headway with the front car, to avoid rear-end crashes or sequential crashes in a tunnel. In addition, a stricter punishment scheme for speeding in tunnels is suggested to be implemented, as the results indicated that speed limit was more effective in tunnels than general freeways.

The crash-level information in the dataset was the most disaggregated data that one could possibly acquire for modeling injury severity in this study, and thus the injury severity model was on a crash-level. Further studies could establish multi-level models, i.e., combining crash level, vehicle level and occupant level, for severity of injuries in tunnels based on more detailed injury information. Besides, only the crash information from year 2018 was able to be acquired and analyzed in this study. Multi-year data are suggested to be incorporated upon availability to enlarge the sample size while considering space-time interaction effects for injury severity in freeway tunnels.

Acknowledgements:

This work was supported by the Department of Transportation, Shandong, China under Grant 2019B32; Department of Transportation, Guizhou, China under Grant 2020-141-022. We would also like to acknowledge the Guizhou Transport Information and Emergency Control Center for providing the crash database.

References

Abegaz, T., Berhane, Y., Worku, A., Assrat, A., & Assefa, A. (2014). Effects of excessive speeding and falling asleep while driving on crash injury severity in Ethiopia: A generalized ordered logit model analysis. *Accident Analysis & Prevention, 71*, 15-21. doi: https://doi.org/10.1016/j.aap.2014.05.003

Aldred, R., Garcia-Herrero, S., Anaya, E., Herrera, S., & Mariscal, M. A. (2019). Cyclist injury severity in Spain: A Bayesian analysis of police road injury data focusing on involved vehicles and route environment. *International Journal of Environment Research and Public Health, 17*(1). doi: 10.3390/ijerph17010096

Amundsen, F., & Ranes, G. (2000). Studies on traffic accidents in Norwegian road tunnels. *Tunnelling and Underground Space Technology, 15*(1), 3-11.

Anastasopoulos, P. C., & Mannering, F. (2009). A note on modeling vehicle accident frequencies with random-parameters count models. *Accident Analysis & Prevention, 41*(1), 153-159. doi: 10.1016/j.aap.2008.10.005

Besharati, M. M., Tavakoli Kashani, A., & Washington, S. (2020). A comparative analysis of road safety across the provinces of Iran from 2005 to 2015. *International Journal of Sustainable Transportation*, 1-9.

Caliendo, C., & De Guglielmo, M. L. (2012). Accident Rates in Road Tunnels and Social Cost Evaluation. *Procedia - Social and Behavioral Sciences, 53*, 166-177. doi: 10.1016/j.sbspro.2012.09.870

Caliendo, C., De Guglielmo, M. L., & Guida, M. (2013). A crash-prediction model for road tunnels. *Accident Analysis & Prevention, 55*, 107-115. doi: 10.1016/j.aap.2013.02.024

Caliendo, C., De Guglielmo, M. L., & Russo, I. (2019). Analysis of crash frequency in motorway tunnels based on a correlated random-parameters approach. *Tunnelling and Underground Space Technology, 85*, 243-251. doi: 10.1016/j.tust.2018.12.012

Celik, A. K., & Oktay, E. (2014). A multinomial logit analysis of risk factors influencing road traffic injury severities in the Erzurum and Kars Provinces of Turkey. *Accident Analysis & Prevention, 72*, 66-77.

Guizhou Traffic Information and Emergency Control Center (2018). Operation report on Guizhou highway networks 2017.

Chang, F., Li, M., Xu, P., Zhou, H., Haque, M. M., & Huang, H. (2016). Injury severity of motorcycle riders involved in traffic crashes in Hunan, China: A mixed ordered logit approach. *International Jounral of Environmental Research Public Health, 13*(7). doi: 10.3390/ijerph13070714

Chang, L-Y., & Chien, J-T. (2013). Analysis of driver injury severity in truck-involved accidents using a non-parametric classification tree model. *Safety Science, 51*(1), 17-22. doi: https://doi.org/10.1016/j.ssci.2012.06.017

Chen, F., Song, M., & Ma, X. (2019). Investigation on the injury severity of drivers in rear-end collisions between cars using a random parameters Bivariate Ordered Probit Model. *International Journal of Environmental Research and Public Health, 16*(14). doi: 10.3390/ijerph16142632

Daganzo, C. (1992). The cell transmission model. Part I: A simple dynamic representation of highway traffic.

Das, S., Le, M., Pratt, M. P., & Morgan, C. (2020). Safety effectiveness of truck lane restrictions: a case study on Texas urban corridors. *International Journal of Urban Sciences, 24*(1), 35-49. doi: 10.1080/12265934.2019.1585929

Dupont, E., Papadimitriou, E., Martensen, H., & Yannis, G. (2013). Multilevel analysis in road safety research. Accident Analysis & Prevention, 60, 402-411.

Gao, K., Tu, H., Sun, L., Sze, N., Song, Z., & Shi, H. (2019). Impacts of reduced visibility under hazy weather condition on collision risk and car-following behavior: Implications for traffic control and management. *International Journal of Sustainable Transportation*, 1-8.

He, C., Chen, B., Wang, J., & Shi, Y. (2010). Research on allocation of the driver's attention on the tunnel sections of a mountain freeway *ICCTP 2010: Integrated Transportation Systems: Green, Intelligent, Reliable* (pp. 444-452).

Hirata, T., Mahara, T., & Yai, T. (2006). Traffic safety analysis in an underground urban expressway using MOVIC-T4. *Infrastructure Planning Review, 23*, 797-804.

Hou, Q., Tarko, A. P., & Meng, X. (2018). Analyzing crash frequency in freeway tunnels: A correlated random parameters approach. *Accident Analysis & Prevention, 111*, 94-100. doi: 10.1016/j.aap.2017.11.018

Huang, H., & Abdel-Aty, M. (2010). Multilevel data and Bayesian analysis in traffic safety. Accident Analysis & Prevention, 42(6), 1556-1565.

Huang, H., Li, C., & Zeng, Q. (2016). Crash protectiveness to occupant injury and vehicle damage: An investigation on major car brands. *Accident Analysis & Prevention, 86*, 129-136.

Huang, H., Peng, Y., Wang, J., Luo, Q., & Li, X. (2018). Interactive risk analysis on crash injury severity at a mountainous freeway with tunnel groups in China. *Accident Analysis & Prevention, 111*, 56-62. doi: 10.1016/j.aap.2017.11.024

Jo, Y., Kim, J., Oh, C., Kim, I., & Lee, G. (2019). Benefits of travel time savings by truck platooning in Korean freeway networks. *Transport Policy, 83*, 37-45. doi: 10.1016/j.tranpol.2019.09.003

Kim, D. G., Lee, Y., Washington, S., & Choi, K. (2007). Modeling crash outcome probabilities at rural intersections: Application of hierarchical binomial logistic models. Accident Analysis & Prevention, 39(1), 125-134.

Kim, J. K., Kim, S., Ulfarsson, G. F., & Porrello, L. A. (2007). Bicyclist injury severities in bicycle–motor vehicle accidents. Accident Analysis & Prevention, 39(2), 238-251.

Kim, J. K., Ulfarsson, G. F., Kim, S., & Shankar, V. N. (2013). Driver-injury severity in single-vehicle crashes in California: a mixed logit analysis of heterogeneity due to age and gender. Accident Analysis & Prevention, 50, 1073-1081.

Li, Z., Ci, Y., Chen, C., Zhang, G., Wu, Q., Qian, Z. S., ... & Ma, D. T. (2019). Investigation of driver injury severities in rural single-vehicle crashes under rain conditions using mixed logit and latent class models. Accident Analysis & Prevention, 124, 219-229.

Ma, Z., Chien, S. I. J., Dong, C., Hu, D., & Xu, T. (2016). Exploring factors affecting injury severity of crashes in freeway tunnels. *Tunnelling and Underground Space Technology, 59*, 100-104. doi: 10.1016/j.tust.2016.06.013

Ma, Z.-l., Shao, C.-f., & Zhang, S.-r. (2009). Characteristics of traffic accidents in Chinese freeway tunnels. *Tunnelling and Underground Space Technology, 24*(3), 350-355. doi: 10.1016/j.tust.2008.08.004

Mannering, F., & Bhat, C. R. (2014). Analytic methods in accident research: methodological frontier and future directions. *Analytic Methods in Accident Research, 1*, 1-22. doi: 10.1016/j.amar.2013.09.001

Mannering, F., Shankar, V., & Bhat, C. R. (2016). Unobserved heterogeneity and the statistical analysis of highway accident data. *Analytic Methods in Accident Research, 11*, 1-16. doi: 10.1016/j.amar.2016.04.001

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.

Mehri, A., Sajedifar, J., Abbasi, M., Naimabadi, A., Mohammadi, A. A., Teimori, G. H., et al. (2019). Safety evaluation of lighting at very long tunnels on the basis of visual adaptation. *Safety Science, 116*, 196-207. doi: 10.1016/j.ssci.2019.03.018

Meng, F., Wong, S. C., Yan, W., Li, Y. C., & Yang, L. (2019). Temporal patterns of driving fatigue and driving performance among male taxi drivers in Hong Kong: A driving simulator approach. *Accident Analysis & Prevention, 125*, 7-13. doi: 10.1016/j.aap.2019.01.020

Meng, F., Wong, W., Wong, S. C., Pei, X., Li, Y. C., & Huang, H. L. (2017). Gas dynamic analogous exposure approach to interaction intensity in multiple-vehicle crash analysis: Case study of crashes involving taxis. *Analytic Methods in Accident Research, 16*, 90-103. doi: 10.1016/j.amar.2017.09.003

Meng, F., Xu, P., Wong, S. C., Huang, H., & Li, Y. C. (2017). Occupant-level injury severity analyses for taxis in Hong Kong: A Bayesian space-time logistic model. *Accident Analysis & Prevention, 108*, 297-307. doi: 10.1016/j.aap.2017.08.010

Meng, Q., & Qu, X. (2012). Estimation of rear-end vehicle crash frequencies in urban road tunnels. *Accident Analysis & Prevention, 48*, 254-263. doi: 10.1016/j.aap.2012.01.025

Pei, X., Wong, S. C., & Sze, N. N. (2012). The roles of exposure and speed in road safety analysis. *Accident Analysis & Prevention, 48*, 464-471. doi: 10.1016/j.aap.2012.03.005

Richards, P. (1956). Shock waves on the highway. *Operations research, 4*(1), 42-51.

Shaheed, M. S., Gkritza, K., Carriquiry, A. L., & Hallmark, S. L. (2016). Analysis of occupant injury severity in winter weather crashes: A fully Bayesian multivariate approach. *Analytic Methods in Accident Research, 11*, 33-47.

Shimojo, A., Takagi, H., & Onuma, H. (1995). *A simulation study of driving performance* *in long tunnel.* Paper presented at the Pacific Rim TransTech Conference. 1995 Vehicle Navigation and Information Systems Conference Proceedings. 6th International VNIS. A Ride into the Future.

Snijders, T. A., & Bosker, R. J. (1999). An introduction to basic and advanced multilevel modeling. Sage, London. WONG, GY, y MASON, WM (1985): The Hierarchical Logistic Regression. Model for Multilevel Analysis, Journal of the American Statistical Association, 80(5), 13-524.

Sun, Z., Wang, J., Chen, Y., & Lu, H. (2018). Influence factors on injury severity of traffic accidents and differences in urban functional zones: the empirical analysis of Beijing. *International Journal of Environmental Research and Public Health, 15*(12). doi: 10.3390/ijerph15122722

Tay, R., Choi, J., Kattan, L., & Khan, A. (2011). A multinomial logit model of pedestrian–vehicle crash severity. *International journal of sustainable transportation, 5*(4), 233-249.

Törnros, J. (2000). *Effects of tunnel wall pattern on simulated driving behaviour*: Statens väg-och transportforskningsinstitut., VTI EC research 9.

Ministry of Transport (2019). Statistical report on the development of transportation industry 2018.

Ministry of Transport (2004). Code for Design of Road Tunnel. China.

Train, K. E. (2009). Discrete choice methods with simulation. Cambridge university press.

Venkataraman, N. S., Ulfarsson, G. F., Shankar, V., Oh, J., & Park, M. (2011). Model of relationship between interstate crash occurrence and geometrics exploratory insights from random parameter Negative Binomial approach. *Transportation Research Record*(2236), 41-48. doi: 10.3141/2236-05

Washington, S., Karlaftis, M. G., Mannering, F., & Anastasopoulos, P. (2020). Statistical and econometric methods for transportation data analysis. CRC press.

Wu, Q., Chen, F., Zhang, G., Liu, X. C., Wang, H., & Bogus, S. M. (2014). Mixed logit model-based driver injury severity investigations in single-and multi-vehicle crashes on rural two-lane highways. *Accident Analysis & Prevention, 72*, 105-115.

Xu, J., Wali, B., Li, X., & Yang, J. (2019). Injury severity and contributing driver actions in passenger vehicle-truck collisions. Internatioanl Journal of Environemntal Research and *Public Health, 16*(19). doi: 10.3390/ijerph16193542

Yeung, J. S., & Wong, Y. D. (2013). Road traffic accidents in Singapore expressway tunnels. *Tunnelling and Underground Space Technology, 38*, 534-541. doi: 10.1016/j.tust.2013.09.002

Yeung, J. S., & Wong, Y. D. (2014). The effect of road tunnel environment on car following behaviour. *Accident Analysis & Prevention, 70*, 100-109. doi: 10.1016/j.aap.2014.03.014

References

Abegaz, T., Berhane, Y., Worku, A., Assrat, A., & Assefa, A. (2014). Effects of excessive speeding and falling asleep while driving on crash injury severity in Ethiopia: A generalized ordered logit model analysis. *Accident Analysis & Prevention, 71*, 15-21. doi: https://doi.org/10.1016/j.aap.2014.05.003

Aldred, R., Garcia-Herrero, S., Anaya, E., Herrera, S., & Mariscal, M. A. (2019). Cyclist injury severity in Spain: A Bayesian analysis of police road injury data focusing on involved vehicles and route environment. *International Journal of Environment Research and Public Health, 17*(1). doi: 10.3390/ijerph17010096

Amundsen, F., & Ranes, G. (2000). Studies on traffic accidents in Norwegian road tunnels. *Tunnelling and Underground Space Technology, 15*(1), 3-11.

Anastasopoulos, P. C., & Mannering, F. (2009). A note on modeling vehicle accident frequencies with random-parameters count models. *Accident Analysis & Prevention, 41*(1), 153-159. doi: 10.1016/j.aap.2008.10.005

Besharati, M. M., Tavakoli Kashani, A., & Washington, S. (2020). A comparative analysis of road safety across the provinces of Iran from 2005 to 2015. *International Journal of Sustainable Transportation*, 1-9.

Caliendo, C., & De Guglielmo, M. L. (2012). Accident Rates in Road Tunnels and Social Cost Evaluation. *Procedia - Social and Behavioral Sciences, 53*, 166-177. doi: 10.1016/j.sbspro.2012.09.870

Caliendo, C., De Guglielmo, M. L., & Guida, M. (2013). A crash-prediction model for road tunnels. *Accident Analysis & Prevention, 55*, 107-115. doi: 10.1016/j.aap.2013.02.024

Caliendo, C., De Guglielmo, M. L., & Russo, I. (2019). Analysis of crash frequency in motorway tunnels based on a correlated random-parameters approach. *Tunnelling and Underground Space Technology, 85*, 243-251. doi: 10.1016/j.tust.2018.12.012

Celik, A. K., & Oktay, E. (2014). A multinomial logit analysis of risk factors influencing road traffic injury severities in the Erzurum and Kars Provinces of Turkey. *Accident Analysis & Prevention, 72*, 66-77.

Guizhou Traffic Information and Emergency Control Center (2018). Operation report on Guizhou highway networks 2017.

Chang, F., Li, M., Xu, P., Zhou, H., Haque, M. M., & Huang, H. (2016). Injury severity of motorcycle riders involved in traffic crashes in Hunan, China: A mixed ordered logit approach. *International Jounral of Environmental Research Public Health, 13*(7). doi: 10.3390/ijerph13070714

Chang, L-Y., & Chien, J-T. (2013). Analysis of driver injury severity in truck-involved accidents using a non-parametric classification tree model. *Safety Science, 51*(1), 17-22. doi: https://doi.org/10.1016/j.ssci.2012.06.017

Chen, F., Song, M., & Ma, X. (2019). Investigation on the injury severity of drivers in rear-end collisions between cars using a random parameters Bivariate Ordered Probit Model. *International Journal of Environmental Research and Public Health, 16*(14). doi: 10.3390/ijerph16142632

Daganzo, C. (1992). The cell transmission model. Part I: A simple dynamic representation of highway traffic.

Das, S., Le, M., Pratt, M. P., & Morgan, C. (2020). Safety effectiveness of truck lane restrictions: a case study on Texas urban corridors. *International Journal of Urban Sciences, 24*(1), 35-49. doi: 10.1080/12265934.2019.1585929

Dupont, E., Papadimitriou, E., Martensen, H., & Yannis, G. (2013). Multilevel analysis in road safety research. Accident Analysis & Prevention, 60, 402-411.

Gao, K., Tu, H., Sun, L., Sze, N., Song, Z., & Shi, H. (2019). Impacts of reduced visibility under hazy weather condition on collision risk and car-following behavior: Implications for traffic control and management. *International Journal of Sustainable Transportation*, 1-8.

He, C., Chen, B., Wang, J., & Shi, Y. (2010). Research on allocation of the driver's attention on the tunnel sections of a mountain freeway *ICCTP 2010: Integrated Transportation Systems: Green, Intelligent, Reliable* (pp. 444-452).

Hirata, T., Mahara, T., & Yai, T. (2006). Traffic safety analysis in an underground urban expressway using MOVIC-T4. *Infrastructure Planning Review, 23*, 797-804.

Hou, Q., Tarko, A. P., & Meng, X. (2018). Analyzing crash frequency in freeway tunnels: A correlated random parameters approach. *Accident Analysis & Prevention, 111*, 94-100. doi: 10.1016/j.aap.2017.11.018

Huang, H., & Abdel-Aty, M. (2010). Multilevel data and Bayesian analysis in traffic safety. Accident Analysis & Prevention, 42(6), 1556-1565.

Huang, H., Li, C., & Zeng, Q. (2016). Crash protectiveness to occupant injury and vehicle damage: An investigation on major car brands. *Accident Analysis & Prevention, 86*, 129-136.

Huang, H., Peng, Y., Wang, J., Luo, Q., & Li, X. (2018). Interactive risk analysis on crash injury severity at a mountainous freeway with tunnel groups in China. *Accident Analysis & Prevention, 111*, 56-62. doi: 10.1016/j.aap.2017.11.024

Jo, Y., Kim, J., Oh, C., Kim, I., & Lee, G. (2019). Benefits of travel time savings by truck platooning in Korean freeway networks. *Transport Policy, 83*, 37-45. doi: 10.1016/j.tranpol.2019.09.003

Kim, D. G., Lee, Y., Washington, S., & Choi, K. (2007). Modeling crash outcome probabilities at rural intersections: Application of hierarchical binomial logistic models. Accident Analysis & Prevention, 39(1), 125-134.

Kim, J. K., Kim, S., Ulfarsson, G. F., & Porrello, L. A. (2007). Bicyclist injury severities in bicycle–motor vehicle accidents. Accident Analysis & Prevention, 39(2), 238-251.

Kim, J. K., Ulfarsson, G. F., Kim, S., & Shankar, V. N. (2013). Driver-injury severity in single-vehicle crashes in California: a mixed logit analysis of heterogeneity due to age and gender. Accident Analysis & Prevention, 50, 1073-1081.

Li, Z., Ci, Y., Chen, C., Zhang, G., Wu, Q., Qian, Z. S., ... & Ma, D. T. (2019). Investigation of driver injury severities in rural single-vehicle crashes under rain conditions using mixed logit and latent class models. Accident Analysis & Prevention, 124, 219-229.

Ma, Z., Chien, S. I. J., Dong, C., Hu, D., & Xu, T. (2016). Exploring factors affecting injury severity of crashes in freeway tunnels. *Tunnelling and Underground Space Technology, 59*, 100-104. doi: 10.1016/j.tust.2016.06.013

Ma, Z.-l., Shao, C.-f., & Zhang, S.-r. (2009). Characteristics of traffic accidents in Chinese freeway tunnels. *Tunnelling and Underground Space Technology, 24*(3), 350-355. doi: 10.1016/j.tust.2008.08.004

Mannering, F., & Bhat, C. R. (2014). Analytic methods in accident research: methodological frontier and future directions. *Analytic Methods in Accident Research, 1*, 1-22. doi: 10.1016/j.amar.2013.09.001

Mannering, F., Shankar, V., & Bhat, C. R. (2016). Unobserved heterogeneity and the statistical analysis of highway accident data. *Analytic Methods in Accident Research, 11*, 1-16. doi: 10.1016/j.amar.2016.04.001

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.

Mehri, A., Sajedifar, J., Abbasi, M., Naimabadi, A., Mohammadi, A. A., Teimori, G. H., et al. (2019). Safety evaluation of lighting at very long tunnels on the basis of visual adaptation. *Safety Science, 116*, 196-207. doi: 10.1016/j.ssci.2019.03.018

Meng, F., Wong, S. C., Yan, W., Li, Y. C., & Yang, L. (2019). Temporal patterns of driving fatigue and driving performance among male taxi drivers in Hong Kong: A driving simulator approach. *Accident Analysis & Prevention, 125*, 7-13. doi: 10.1016/j.aap.2019.01.020

Meng, F., Wong, W., Wong, S. C., Pei, X., Li, Y. C., & Huang, H. L. (2017). Gas dynamic analogous exposure approach to interaction intensity in multiple-vehicle crash analysis: Case study of crashes involving taxis. *Analytic Methods in Accident Research, 16*, 90-103. doi: 10.1016/j.amar.2017.09.003

Meng, F., Xu, P., Wong, S. C., Huang, H., & Li, Y. C. (2017). Occupant-level injury severity analyses for taxis in Hong Kong: A Bayesian space-time logistic model. *Accident Analysis & Prevention, 108*, 297-307. doi: 10.1016/j.aap.2017.08.010

Meng, Q., & Qu, X. (2012). Estimation of rear-end vehicle crash frequencies in urban road tunnels. *Accident Analysis & Prevention, 48*, 254-263. doi: 10.1016/j.aap.2012.01.025

Pei, X., Wong, S. C., & Sze, N. N. (2012). The roles of exposure and speed in road safety analysis. *Accident Analysis & Prevention, 48*, 464-471. doi: 10.1016/j.aap.2012.03.005

Richards, P. (1956). Shock waves on the highway. *Operations research, 4*(1), 42-51.

Shaheed, M. S., Gkritza, K., Carriquiry, A. L., & Hallmark, S. L. (2016). Analysis of occupant injury severity in winter weather crashes: A fully Bayesian multivariate approach. *Analytic Methods in Accident Research, 11*, 33-47.

Shimojo, A., Takagi, H., & Onuma, H. (1995). *A simulation study of driving performance* *in long tunnel.* Paper presented at the Pacific Rim TransTech Conference. 1995 Vehicle Navigation and Information Systems Conference Proceedings. 6th International VNIS. A Ride into the Future.

Snijders, T. A., & Bosker, R. J. (1999). An introduction to basic and advanced multilevel modeling. Sage, London. WONG, GY, y MASON, WM (1985): The Hierarchical Logistic Regression. Model for Multilevel Analysis, Journal of the American Statistical Association, 80(5), 13-524.

Sun, Z., Wang, J., Chen, Y., & Lu, H. (2018). Influence factors on injury severity of traffic accidents and differences in urban functional zones: the empirical analysis of Beijing. *International Journal of Environmental Research and Public Health, 15*(12). doi: 10.3390/ijerph15122722

Tay, R., Choi, J., Kattan, L., & Khan, A. (2011). A multinomial logit model of pedestrian–vehicle crash severity. *International journal of sustainable transportation, 5*(4), 233-249.

Törnros, J. (2000). *Effects of tunnel wall pattern on simulated driving behaviour*: Statens väg-och transportforskningsinstitut., VTI EC research 9.

Ministry of Transport (2019). Statistical report on the development of transportation industry 2018.

Ministry of Transport (2004). Code for Design of Road Tunnel. China.

Train, K. E. (2009). Discrete choice methods with simulation. Cambridge university press.

Venkataraman, N. S., Ulfarsson, G. F., Shankar, V., Oh, J., & Park, M. (2011). Model of relationship between interstate crash occurrence and geometrics exploratory insights from random parameter Negative Binomial approach. *Transportation Research Record*(2236), 41-48. doi: 10.3141/2236-05

Washington, S., Karlaftis, M. G., Mannering, F., & Anastasopoulos, P. (2020). Statistical and econometric methods for transportation data analysis. CRC press.

Wu, Q., Chen, F., Zhang, G., Liu, X. C., Wang, H., & Bogus, S. M. (2014). Mixed logit model-based driver injury severity investigations in single-and multi-vehicle crashes on rural two-lane highways. *Accident Analysis & Prevention, 72*, 105-115.

Xu, J., Wali, B., Li, X., & Yang, J. (2019). Injury severity and contributing driver actions in passenger vehicle-truck collisions. Internatioanl Journal of Environemntal Research and *Public Health, 16*(19). doi: 10.3390/ijerph16193542

Yeung, J. S., & Wong, Y. D. (2013). Road traffic accidents in Singapore expressway tunnels. *Tunnelling and Underground Space Technology, 38*, 534-541. doi: 10.1016/j.tust.2013.09.002

Yeung, J. S., & Wong, Y. D. (2014). The effect of road tunnel environment on car following behaviour. *Accident Analysis & Prevention, 70*, 100-109. doi: 10.1016/j.aap.2014.03.014

Conflict of Interest

The authors declare no conflict of interest.