TECHNICAL PAPER

JOURNAL OF THE SOUTH AFRICAN INSTITUTION OF CIVIL ENGINEERING

ISSN 1021-2019

Vol 64 No 1, March 2022, Pages 63–70, Paper 1174

What leads to severe multi-vehicle crashes on mountainous expressways in Western China?

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This paper investigates the occurrence and severity of collisions involving multiple vehicles on mountain expressways (MMEs) in Western China. A total of 1 521 crash samples occurring on one typical mountain expressway in Shaanxi, China, between 2012 and 2017, were analysed through a partially constrained generalised ordered logit to identify the significant risk factors contributing to the severity of such crashes. Elasticity analysis was performed to quantify the effects of each independent explanatory variable on the collision severity outcomes. Fourteen total explanatory variables were found to have a significant and pronounced influence on the likelihood of MME crashes. These include the type of collision, the at-fault driver's age, driving while fatigued, cell phone use while driving, alcohol-impaired driving, speeding, risky following and dangerous overtaking behaviour, sharp curves in the roadway and slippery pavement conditions, seasons, day of the week, time of day, and adverse weather (rain/snow/fog). The impacts of the variables on the collision severity were also explored. Taken together, the findings may serve as a useful guide for developing legislation and technical countermeasures to ensure traffic safety on mountain expressways in Western China.

INTRODUCTION

The number of registered motor vehicles has increased dramatically in China over the past two decades. Numbers have soared from about 9.6 million in 2003 to more than 327 million in 2018, an almost 32-fold increase (National Bureau of Statistics of China 2019), which in turn resulted in a great number of road motor traffic crashes (Benlagha & Charfeddine 2020). In 2018 a total of 244 937 road motor traffic crashes occurred, with 258 532 injuries, 63 194 fatalities, and direct economic loss of 0.221 billion US dollars in China. A large proportion of these records were identified as occurring along roads in mountainous areas (National Bureau of Statistics of China 2019). Alarming statistics in China show that mountainous expressways are susceptible to a high frequency of multi-vehicle crashes, as well as more severe consequences (Zhang *et al* 2016; Meng 2017).

Unlike single-vehicle crashes resulting from loss of vehicle control associated with driver error or negligence like excessive speed, alcohol usage and driving fatigue (Rusli *et al* 2017), it is extremely difficult to determine the causes of multi-vehicle crashes, especially when occurring on mountainous expressways, due to the adverse traffic environment of the terrain, which includes tight curves, steep slopes, the existence of bridges and tunnels, and changing climatic conditions (Meng 2017; Wang & Prato 2019; Wang *et al* 2019a). The huge economic loss and serious social repercussions that are incurred by crashes involving multiple vehicles have attracted increasing attention worldwide from researchers and traffic managers (Wang & Prato 2019; Wang *et al* 2019a; Dong *et al* 2018; Rezapour *et al* 2019), especially for those occurring on mountainous expressways. Therefore, the potential risk factors associated with these crashes must be identified to better understand how they occur, and to suggest suitable countermeasures.

In recent years, considerable research efforts have focused on investigating the geometric characteristics of roadways that may contribute to the occurrence of MME crashes (Yu *et al* 2015). For example, Rusli *et al* (2018) examined MME crashes in Malaysia and found that the presence of minor junctions enhances the likelihood of MME crashes, while the existence of horizontal curves along a steep gradient, and the presence of a passing lane, increase

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Keywords: multiple-vehicle crash, mountain expressway, risk factor, partially constrained generalised ordered logit model, elasticity analysis

the likelihood of such crashes (Rusli *et al* 2018). Additionally, weather and traffic-related factors, such as rainfall (Rusli *et al* 2018), visibility (Yu *et al* 2015), pavement surface conditions (Ma *et al* 2016; Wang *et al* 2021b) and annual average daily traffic (Sameen & Pradhan 2017), influence the occurrence of MME crashes significantly. In Chongqing, China, the season, time of the crash, involvement of trucks, crash features, weather, and roadway conditions have been found to have obvious impacts on the levels of MME crashes (Meng 2017). Driver factors are also frequently explored by researchers. Zhang *et al* (2016) investigated MME crash data from the Taigan Expressway in Jiangxi, China, finding that younger and older drivers, especially female drivers, contribute more to severe MME crashes (Meng 2017). Rusli *et al* (2018) showed that driver speeding significantly increased the injury severity in MME crashes. Wang *et al* (2019a) and Dong *et al* (2018) found that truck drivers' age, seatbelt status, and speeding and risky following behaviour significantly correlated with severe crashes on mountainous expressways.

According to China's administrative division, China's western region embraces the six provinces of Shaanxi (SX), Gansu (GS), Qinghai (QH), Sichuan (SC), Yunnan (YN) and Guizhou (GZ); the five autonomous regions of Guangxi (GX), Ningxia (NX), Inner Mongolia (IM), Xinjiang (XJ) and Tibet (TI); and the Chongqing (CQ) Municipality as the red-marked area in Figure 1 (excluding the South China Sea) – a land area of 6.86 million square kilometres, accounting for 70.6% of the country's total land area. Much of the Western China territory (81.9%) is mountainous, and unfortunately few studies over the past several years have focused on a quantitative impact analysis of the various potential factors that contribute to MME crashes in this vast area (Wang *et al* 2021a) where at-fault driver behaviour, geometric design elements, and environmental conditions are unique from other areas.

Shaanxi Province (SX) – located in the heart of China, straddling the Loess Plateau, Guanzhong Plains and Qinba Mountains from north to south, with complex topography and landscape – has seen a representative number of MME crashes (Wang & Prato 2019; Wang *et al* 2019a; 2021b). Using reported multi-vehicle crash data from one typical mountainous expressway in Shaanxi, China, over a recent six-year time frame, the primary purpose of this study was therefore to apply a generalised ordered logit model to quantify the potential risk factors associated with the severity of MME crashes, the severity of collisions resulting from these crashes, and the marginal effects of each explanatory factor on MME crash severity. It is anticipated that the findings presented here can be used to guide the development of legislations and technical countermeasures for traffic safety on mountainous expressways in Western China.

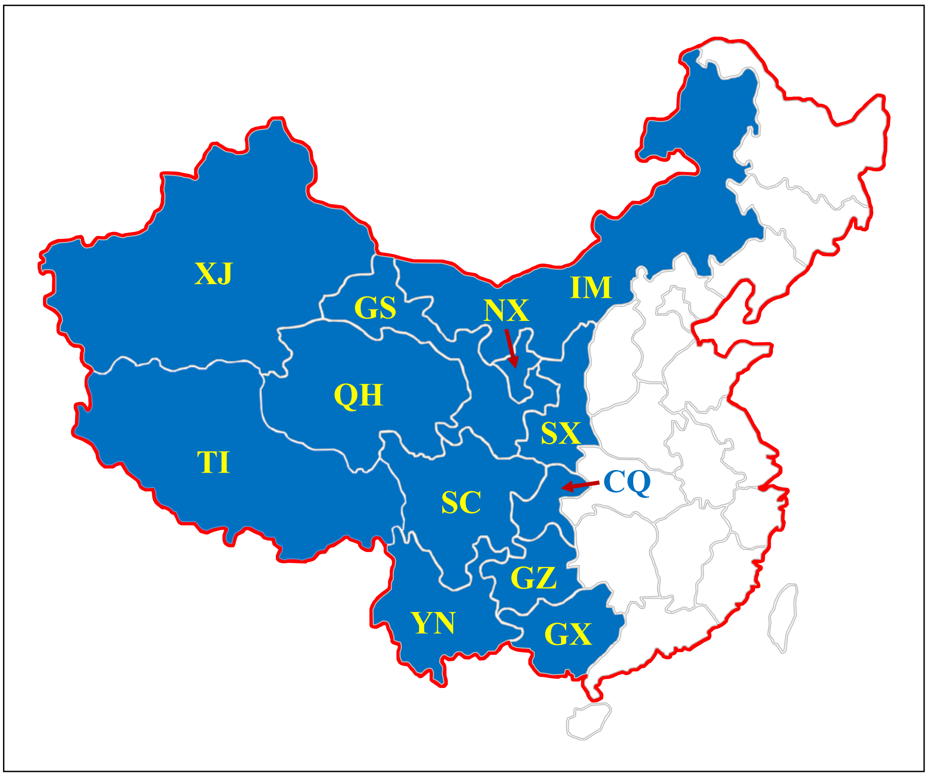

Figure 1 The western region of China mainland

Figure 2 One typical mountainous expressway segment in Shaanxi Province, China

METHODOLOGY

Data collection

A total of 1 705 police-reported multi-vehicle crashes between 2012 and 2017, accounting for 63.01% of the total observations, were collected from the Xihan Expressway in Shaanxi (SX), China. This stretch of road (shown in Figure 2) is a four-lane 198.5 km segment of the G5 Jingkun Expressway from Laoyukou Toll Station (K1131+657) to Xiejiaying Interchange (K1330+204), with a speed limit of 60 ~ 80 km/h. Among the MME

Table 1 Contributory variable description

Variable	Code	Frequency	%	Code	Frequency	%
Crash feature						
Severity	1 = PDO 3 = Fatality	767 291	50.43 19.13	2 = Injury	463	30.44
Type of collision	1 = Head-on 3 = Sideswipe*	173 200	11.37 13.15	2 = Rear-end 4 = Angle	1040 108	68.38 7.10
Driver factor						
Gender	0 = Female	141	9.27	1 = Male	1380	90.73
Age	1 = Young* 3 = Old	355 72	23.34 4.73	2 = Adult	1094	71.93
Driving while fatigued	0 = No	1403	92.24	1 = Yes	118	7.76
Cell phone use	0 = No	1441	94.74	1 = Yes	80	5.26
Alcohol use	0 = No	1438	94.54	1 = Yes	83	5.46
Vehicle factor						
Truck involved	0 = No	991	65.15	1 = Yes	530	34.85
Speeding	0 = No	1383	90.93	1 = Yes	138	9.07
Risky following	0 = No	1345	88.43	1 = Yes	176	11.57
Dangerous overtaking	0 = No	1416	93.10	1 = Yes	105	6.90
Roadway factor						
Sharp curve	0 = No	815	53.58	1 = Yes	706	46.42
Steep slope	0 = No	759	49.90	1 = Yes	762	50.10
Pavement condition	0 = Dry	1023	67.26	1 = Slippery	498	32.74
Environmental factors						
Seasons	1 = Spring* 3 = Autumn	298 472	19.59 31.03	2 = Summer 4 = Winter	374 377	24.59 24.79
Day of week	0 = Working days	1032	67.85	1 = Weekends / holidays	489	32.15
Time of day	1 = 06:00–18:00* 3 = 24:00–06:00	823 354	54.11 23.27	2 = 18:00–24:00	344	22.62
Weather	0 = Clear	1223	80.41	1 = Adverse	298	19.59

*base

crash records, 184 cases were deleted due to containing incomplete information, meaning that 1 521 cases were included in the final database.

A three-point ordinal scale was used to classify the MME crash severities measured by the most severely injured person(s), including: (a) property damages only (PDO), in which there were only damage to road facilities and vehicles or negligible personal injuries, (b) injury, in which there were personal injuries requiring hospitalisation, together with serious property damage, and (c) fatality, in which there were persons killed immediately or persons who died within 30 days as a result of the crash (Wang & Prato 2019; Wang *et al* 2019a).

The distribution of the crash severity levels was as follows: PDO (50.43%), injury (30.44%) and fatality (19.13%). Four types of collisions were considered for further analysis, namely, head-on, rear-end, sideswipe, and angle.

Additionally, the crash database collected information related to at-fault driver demographic characteristics and driving behaviour, vehicle attributes, roadway conditions, and environmental influence, as shown in Table 1. The information correlated to the roadway geometric factors was determined by the original expressway design documents and updated through the latest Google Earth, and the rest was directly extracted from the original accident reports released by the local traffic management departments. Additional information included:

- At-fault driver factors: gender, age (e.g. < 30 years old, 30–50 years old, and > 50 years old), driving fatigue, impairment by alcohol, and cell phone usage
- Vehicle factors: truck involvement, speeding and risky following, and dangerous overtaking
- Roadway factors: sharp curves (radius of horizontal curve < 2 000 m), steep slope (longitudinal gradient > 3%), and slippery pavement due to weather.
- Environmental factors: seasons (e.g. spring: March to May, summer: June to August, autumn: September to November, and winter: December to February), day of the week (including working days = 0:00 Monday to 16:59 Friday, weekends/holidays = 17:00 Friday to 24:00 Sunday, and public holidays including New Year, Chinese New Year, Qingming Festival, International Labour

Day, Duanwu Festival, Mid-Autumn Festival, and National Day), time of day (e,g, 6:00–18:00, 18:00–24:00, 24:00–6:00), weather (including clear: sunny/cloudy, and adverse: rainy/snowy/foggy).

Analytical model

Since the crash severity data is typically ordinal, varying from a non-fatal to fatal level in nature, traditionally ordered (both probit and logit) probability models were employed in the literature to model the severity of traffic crashes (Zhang *et al* 2016; Dong *et al* 2018; Rezapour *et al* 2019; Wang *et al* 2021b; Kahn & Vachal 2020).

Let y_i be the MME crash severity with three categories (PDO, injury and fatal), and x_i be the potential variables affecting the MME crash severity. A latent variable y_i^* can then be used to measure the MME crash severity through an ordered logit approach:

$$y_i^* = x_i'\beta + \varepsilon_i \tag{1}$$

where $x_i = \{1, x_{i1}, x_{i2}, \ldots, x_{iN}\}^{\mathrm{T}}$ is a vector representing the values of crash i on the full set of N independent explanatory variables, $\beta = \{\beta_0, \beta_1, \beta_2, \ldots, \beta_N\}^{\mathrm{T}}$ is a vector of regression parameters to be estimated, and ε_i is a random error term with standard logistic distribution.

The relationship between the observed levels of the dependent injury severity y_i and the latent injury risk y_i^* can be expressed by introducing the thresholds α_1 and α_2 as follows:

$$y_i = 1 \text{ (PDO)}, \quad \text{if } y_i^* \ll \alpha_1 \tag{2a}$$

$$y_i = 2 \text{ (injury)}, \quad \text{if } \alpha_1 < y_i^* \ll \alpha_2 \tag{2b}$$

$$y_i = 3 \text{ (fatal)}, \quad \text{if } y_i^* > \alpha_2 \tag{2c}$$

Thus, the probability P of MME crash i having a severity level j can also be expressed as:

$$P(y_i > j) = g(x_i'\beta_j) = \frac{\exp(\alpha_j - x_i'\beta_j)}{1 + \exp(\alpha_j - x_i'\beta_j)}, j = 1,2,3 \tag{3}$$

where α_j is a cut-off point for the j^{th} cumulative logit.

It should be noted that Equation 1 should meet the parallel-lines assumption, which requires that the estimated parameters remain the same for different severity levels (Wang *et al* 2019a). However, such an assumption is often violated, so a partially constrained generalised ordered logit (PCGOL) model, also known as the gamma parameterisation of partial proportional odds model with logit function, was proposed, which allowed the parallel-lines assumption to be relaxed for one or a few dependent variables but retained the ordered nature for the majority of dependent variables on a set of n independent explanatory variables (Peterson & Harrel 1990) as:

$$P(y_i > j) = g(x'_i\beta_j) = \frac{\exp[\alpha_j - (x_i'\beta_j + z_i'\gamma_j)]}{1 + \exp[\alpha_j - (x_i'\beta_j + z_i'\gamma_j)]}, j = 1,2,3 \tag{4}$$

where β_j is a vector of coefficients correlated with a subset x_i of independent explanatory variables (see Table 1) for which the parallel-lines assumption is not violated, and γ_j is a vector of coefficients correlated with a subset z_i of independent explanatory variables for which the parallel-lines assumption is violated.

The violation of the parallel-lines assumption was firstly checked for each independent variable and then the two parameter vectors β_j and γ_j and cut-off thresholds α_j were estimated via the maximum of the log likelihood function LL (Peterson & Harrel 1990). In the proposed model, each explanatory variable has one β coefficient and (k-2)γ coefficients, where k is 3 in the current research as the number of alternatives. There were (k-1)α coefficients reflecting the cut-off points.

Equivalently, Equation 4 can be rewritten using the cumulative probability distribution as:

$$P(y_i \ll j) = 1 - g(x_i'\beta_j) = F(\alpha_j - x_i'\beta_j), j = 1,2,3 \tag{5}$$

which can also be expressed in Equations 6a – 6c:

$$P(y_i = 1) = F(\alpha_1 - x_i'\beta_1) \tag{6a}$$

$$P(y_i = 2) = F(\alpha_2 - x_i'\beta_2) - F(\alpha_1 - x_i'\beta_1) \tag{6b}$$

$$P(y_i = 3) = 1 - F(\alpha_2 - x_i'\beta_2) \tag{6c}$$

Elasticity analysis

Additionally, each independent variable (see Table 2) is transferred into a binary categorical explanatory variable in determining the partial proportional odds model; the elasticity cannot be measured since it is not differentiable, so the direct pseudo-elasticity analysis is conducted to quantify the marginal effect of independent variable n on the probability of severity level j for MME crash i. The percentage change in probability specific to severity level j for MME crash i was calculated when the n^{th} binary variable x_{jin} ($n \ll N$) was switched from 0 to 1 or vice versa (Wang & Prato 2019):

$$E_{x_{jin}}^{P(y_i > j)} = \frac{P(y_i > j)[given\ x_{jin} = 1] - P(y_i > j)[given\ x_{jin} = 0]}{P(y_i > j)[given\ x_{jin} = 0]} \tag{7}$$

The pseudo-elasticities were calculated for each severity level j and MME crash i, and consequently averaged for each MME crash severity j over all crash samples.

RESULTS AND DISCUSSION

Model estimation

The partial proportional odds model was estimated via a user-written gologit2 procedure in Stata 15 statistical software (Peterson & Harrel 1990), when explanatory variables were progressively added to the model while testing the violation of the parallel-lines assumption using the 0.05 level of significance. Such an interactive procedure was performed to find the best model until no further variable significantly improved the fit of model. Finally, the best fit model is presented in Table 2.

Fourteen total explanatory variables, including type of collision, at-fault driver's age, driving while fatigued, cell phone use while driving, alcohol-impaired driving, speeding, risky following and dangerous overtaking behaviour, sharp curves in the roadway and slippery pavement conditions, seasons, day of the week, time of day and adverse weather, were all found to be significantly associated with MME crash severity. Four variables, namely at-fault driver's speeding, overtaking behaviour, sharp curves, and time of day violated the proportional odds assumption (see Table 2). The marginal effects of each explanatory variable on the probability of MME crash severity level at 95% confidence level are presented in Table 3.

Collision characteristics

The type of collision was classified into four categories: head-on, rear-end, sideswipe and angle, with sideswipe as the reference category. Significant difference was observed between head-on and sideswipe

Table 2 Estimation results of the PCGOL model

Explanatory variables	Est.	S.E.	Explanatory variables	Est.	S.E.
Beta			Time of day 18:00-24:00	0.733**	0.229
Type of collision Head-on	1.259**	0.401	24:00-06:00	2.891***	0.356
Age > 50	1.292**	0.403	Adverse weather	1.740***	0.250
Driving while fatigued	3.836***	0.395	**Gamma**		
Cell phone use	2.988***	0.489	Speeding	1.128*	0.524
Alcohol use	3.173***	0.412	Overtaking	–2.199**	0.679
Speeding	1.409**	0.425	Sharp curve	–2.006***	0.361
Risky following	2.171***	0.295	Time of day 24:00–06:00	–1.934***	0.425
Dangerous overtaking	2.660***	0.516	**Alpha**		
Sharp curve	3.396***	0.286	α_1	–5.756***	0.568
Slippery pavement	1.826***	0.238	α_2	–9.425***	0.757
Seasons Summer	1.808***	0.321	**Fit-of-goodness**		
Winter	2.481***	0.328	$LL(0)$	–1 557.06	
Weekends / holidays	0.929**	0.272	$LL(\beta)$	–474.90	
			Pseudo R^2	0.695	
*p < 0.05; **p < 0.01; ***p < 0.001					

Table 3 Marginal effects and standard errors of the PCGOL model

Explanatory variable		PDO	Injury	Fatality
Type of collision	Head-on	–0.053** (0.017)	–0.011* (0.005)	0.064** (0.020)
Age	More than 50	–0.055** (0.017)	–0.011* (0.006)	0.066** (0.021)
Driving while fatigued		–0.163*** (0.012)	–0.034* (0.013)	0.196*** (0.019)
Cell phone use		–0.127*** (0.020)	–0.026* (0.011)	0.153*** (0.025)
Alcohol use		–0.135*** (0.017)	–0.028* (0.012)	0.162*** (0.021)
Speeding		–0.060** (0.018)	–0.070** (0.025)	0.130*** (0.019)
Risky following		–0.092*** (0.012)	–0.019* (0.008)	0.111*** (0.016)
Dangerous overtaking		–0.113*** (0.021)	0.089** (0.032)	0.024 (0.025)
Sharp curve		–0.144*** (0.009)	0.073** (0.023)	0.071** (0.022)
Slippery pavement		–0.077*** (0.010)	–0.016* (0.006)	0.093*** (0.012)
Seasons	Summer	–0.077*** (0.013)	–0.016* (0.007)	0.093*** (0.017)
	Winter	–0.105*** (0.014)	–0.022* (0.009)	0.127*** (0.017)
Weekends/holidays		–0.039** (0.011)	0.031 (0.017)	0.009 (0.013)
Time	18:00–24:00	–0.031** (0.010)	-0.006* (0.003)	0.038** (0.012)
	24:00–06:00	–0.123*** (0.014)	0.074*** (0.019)	0.049*** (0.014)
Adverse weather		–0.074*** (0.012)	-0.015** (0.005)	0.089*** (0.011)
* p < 0.05; ** p < 0.01; *** p < 0.001				

collisions, but not between rear-end and sideswipe collision, or between angle and sideswipe collision. The head-on collision type displayed a significant and positive coefficient (estimate = 1.259, p-value = 0.002), indicating that at-fault drivers involved in a head-on collision are likely to sustain more severe crashes than those of a sideswipe collision, which is in good agreement with previous findings from Shaanxi, China (Chen & Zhang 2016). Specifically, a decrease of 5.3% in PDO collision and 1.1% in injury collision, and an increase of 6.4% in fatal collision were observed for MME crashes with head-on collision type.

Driver factors

The at-fault driver's age was divided into three levels – less than 30 years, 30–50 years and more than 50 years, and the first level was selected as the reference age. There was a significant difference visible between more than 50 years and less than 30 years, but not between 30–50 years and less than 30 years. The at-fault driver's age of more than 50 years was found to have significant and intensifying influence on the collision severity (estimate = 1.292, p-value = 0.001). This indicates that older at-fault drivers are more likely to sustain more severe crashes, which is consistent with previous findings (Zhang *et al* 2016; Wang *et al* 2019a). The at-fault driver's age of more than 50 years decreases the probability of PDO and injury collisions by 5.5% and 1.1%, respectively, but increases the probability of fatal collision by 6.6% (see Table 3). A possible explanation is that truck drivers are more easily fatigued while driving on monotonous mountainous expressways for long hours, thus becoming progressively less sensitive to emergency conditions.

As expected, the influence of the at-fault driver's driving while fatigued (est. = 3.836, p-value < 0.001), cell phone use while driving (est. = 2.988, p-value < 0.001), alcohol-impaired driving (est. = 3.173, p-value < 0.001), and risky following (est. = 2.171, p-value < 0.001) behaviour has a significantly positive correlation with collision severity. Accordingly, it can be inferred that at-fault drivers who are engaged in these risky types of driving behaviour are more likely to sustain severe injuries in MME crashes. The marginal effects analysis also shows that these four risky driving behaviours significantly enhance the probability of fatal collision but reduce the probability of PDO and injury collisions in MME crashes, as shown in Table 3. As an example, at-fault driver's behaviour while driving when fatigued increases the chance of fatal collision by 19.6%, while reducing the chance of PDO collision by 16.3%, and injury collision by 3.4%, respectively. Similar findings have previously been reported by numerous researchers (Wang & Prato 2019; Wang *et al* 2019a & 2019b; Chen & Zhang 2016). These results strongly suggest that strict laws and regulations should be enforced to prohibit risky driving behaviour, especially for inexperienced and elderly drivers while navigating sharp curves and steep downhill gradients under adverse weather conditions (i.e. slippery pavement, heavy rain or snow, and low visibility).

Additionally, at-fault drivers' speeding behaviour is shown to have a significant and pronounced influence on MME crash severity but violates the proportional odds assumption. The first panel of coefficient (i.e. PDO versus injury + fatality) is 1.409 (p-value = 0.001), and the second panel of coefficient (i.e. PDO + injury versus fatality) is 2.537; thus it can be concluded that at-fault drivers who engage in speeding behaviour are likely to sustain more fatal collisions in MME crashes (Wang & Prato 2019; Wang *et al* 2019a; Theofilatos *et al* 2018). An increase of 13.0% in fatal collisions, and a decrease of 6.0% in PDO collisions and 7.0% in injury collisions were observed for MME crashes due to at-fault drivers' speeding behaviour (see Table 3). Dangerous overtaking behaviour was also found to violate the proportional odds assumption, and the descending series of coefficients (2.660 versus 0.461) indicated that at-fault drivers were likely to sustain more injury collisions, which considerably altered the probabilities of certain crash severity (PDO: −11.3%; injury: 8.9%; fatality: 2.4%). This is consistent with previous reporting (Richter *et al* 2017). On the other hand, truck involvement was not found to show significant influence on MME crash severity, and a recent examination of a Greek crash sample also exhibited that an increased proportion of trucks do not result in more severe injuries (Theofilatos *et al* 2018).

Roadway contributions

Regarding road factors, a sharp curve violates the proportional odds assumption and has a significant and positive impact on MME crash severity p-value < 0.001. Specifically, the decreasing trend of panels of coefficient (3.396 versus 0.390) shows that MME crashes occurring on sharp curves are more likely to result in injury collisions, which is consistent with its marginal effects (see Table 3). These results correspond well with many previous findings reported in literature (Meng 2017; Rusli *et al* 2018; Wang & Prato 2019; Wang *et al* 2019a; Yu *et al* 2015; Chen & Zhang 2016). Steep slopes, however, were not found to have significantly correlated with fatality and injury probabilities in discordance with previous results (Wang *et al* 2019a; Yu *et al* 2015; Chen & Zhang 2016). The possible reason may be that the later model structure does not consider the different mechanism between single-vehicle and multi-vehicle crashes on mountainous expressways. In addition, slippery pavement conditions have a significantly positive influence on crash severity (est. = 1.826, p-value < 0.001), increasing the probability to 9.3% in fatal collisions, while decreasing the probability to 47.7% and 1.6% in PDO and injury collisions, respectively. Many previous reports in literature have also confirmed this result (Wang & Prato 2019; Ma *et al* 2016; Chen & Zhang 2016).

Environmental conditions

Season is naturally split into four categories: spring, summer, autumn and winter, and spring was selected as the reference category in this study. The modelling result revealed that there was a significant difference between summer and spring, as well as winter and spring, but not between autumn and spring. Particularly, both summer (est. = 1.808, p-value < 0.001) and winter (est. = 2.481, p-value < 0.001) were significantly and positively correlated with crash severity, indicating that an MME crash occurring on a summer or winter's day is likely to be a more serious collision compared to that happening on a spring day. This considerably alters the probabilities of certain crash severities (PDO: −7.7% versus −10.5%; injury: −1.6% versus −2.2%; fatality: 9.3% versus 12.7%), as shown in Table 3. The possible reason lies in the adverse effects of rainfall, fog and snowfall on at-fault driver's peripheral vision and vehicle brake performance; however, most at-fault drivers comprehend the risk of driving under adverse weather conditions on summer or winter days, so they may drive carefully and thus the total number of crash occurrences could be reduced, but not the crash severity. This result contradicts our previous finding from Taigan Expressway, a segment of G45 Daguang Expressway from Taihe to Ganzhou in Jiangxi, China (Zhang *et al* 2016).

Evidently, the period between midnight and six in the early morning is the most dangerous time for drivers due to sleepiness or fatigue while driving (Zhang *et al* 2016; Meng 2017; Wang & Prato 2019; Wang *et al* 2019a; Chen & Zhang 2016) and violates the proportional odds assumption with a positive coefficient (est. = 2.891, p-value < 0.001). As the first panel of coefficient (2.891) is larger than the second one (0.957), it can be inferred that MME crashes occurring during the period of midnight to 6:00 am are likely to result in more injury collisions, increasing the likelihood of injury and fatal collisions by 7.4% and 4.9%, respectively, while decreasing the probability of PDO collision by 12.3%. This is mainly attributed to at-fault driver sleepiness or fatigue while driving, as well as darkness or low-light conditions. During this period, at-fault drivers often use alcohol, caffeine, or music to keep themselves awake, but these measures can significantly distract attention and impair driving performance (Ronen *et al* 2014). Thus, drivers should be educated against continuous driving while fatigued or sleepy. Specifically, it is recommended that the government should formulate strict rules and regulations to limit maximum nightly driving hours and minimum rest hours after continuous or accumulated driving, especially for those who engage in long-distance commercial transport, and any offenders should be seriously punished.

Conversely, the period from 6:00 pm to midnight does not violate the proportional odds assumption and is significantly and positively correlated with crash severity (est. = 0.733, p-value = 0.001). Also, as illustrated in the results of marginal effects (see Table 3), a reduction of 3.1% in PDO collision and 0.6% in injury collision, as well as an increase of 3.8% in fatal collision, were observed in MME crashes associated with the period from 6:00 pm to midnight.

Finally, adverse weather conditions (est. = 1.740, p-value < 0.001) were illustrated to have a significantly positive association with collision severity, which indicated that MME crashes under adverse conditions (rain, snow or fog) are likely to cause severe collisions, increasing the chance of fatal collision by 8.9%, but reducing the possibility of PDO and injury collisions by 7.4% and 1.5%, respectively. Obviously, driving under adverse conditions may increase the risk of crashes due to the reduced sight distance, slippery pavement and limited vehicle manoeuvrability along horizontal and crest vertical curves on mountainous expressways. This finding is consistent with many previous reports (Zhang *et al* 2016; Meng 2017; Rusli *et al* 2018: Wang & Prato 2019; Wang *et al* 2019a; Yu *et al* 2015; Chen & Zhang 2016).

CONCLUSION

This research examined the influence of potential risk factors on MME crash severity, as well as the marginal effects of each contributory factor, by combining 1 521 multi-vehicle crash samples from one typical mountainous expressway in Shaanxi, China, and utilising a partially constrained generalised ordered logit model. The statistical results illustrate that fourteen independent contributory variables had a significant and intensifying influence on MME crash severity.

An extremely significant contribution lies in the findings about the at-fault driver's risky driving behaviour on the fatality probability upon an MME crash occurrence. There appears to be an urgent need for enforcement measures to discourage such risky driving behaviour like driving while fatigued, cell phone use while driving, alcohol-impaired driving, speeding, and risky following, especially among those engaged in long-distance commercial transport tasks. Another very significant contribution lies in the findings about the effects of roadway geometric characteristics and environmental conditions. The results also suggest that stricter police enforcement should be compelling at slippery and sharp curve segments during adverse weather and in winter.

This study is not without important methodological limitations, however. Firstly, the crash sample was only selected from one expressway segment in Shaanxi, China, and may not be representative of the overall traffic safety situation on mountainous expressways in the country as a whole. In addition, the original data may contain some missing, incomplete, or possibly incorrect points due to unreported crashes or injuries and errors involved in manual data entry. Secondly, a relatively small sample (1 705 observations) over a very long period of time (six years) can lead to unreliable and inaccurate estimations (Behnood & Mannering 2019), but the current study does not test the temporal stability of the estimated parameters over time. It is worth noting that more recent data should be collected for the model estimation in the near future, in which crash data can be divided over different time periods and then likelihood ratio tests will be used to explore whether temporal instability is an issue. Thirdly, the data contains a high level of unobserved heterogeneity, which may affect identifying the exact contributing factors, so the models accounting for heterogeneity in data analysis merit further deep investigation. Finally, the coupling effect of multiple factors on the severity of MME crashes was not focused on in this study, such as the existence of tunnels and bridges (Sun *et al* 2020), so one of the greatest future challenges is to unpack which combinations of factors produce the greatest risks (Boora *et al* 2018; Santos *et al* 2021), such as driver's risk driving behaviour and sharp curves coincided, and traffic flow and weather conditions interacted, etc.

It is anticipated that the findings of this study will provide useful empirical knowledge on the effects of several factors affecting the injury severity of MME crashes. The proposed probabilistic approach assists by providing efficient countermeasures and technical programs for crash prevention and safety performance improvement on mountainous expressways in Western China and other countries in the world.

ACKNOWLEDGEMENTS

This work was financially supported by the Natural Science Foundation of Shaanxi Province, China, under Grant Number 2020JM-252. The authors acknowledge the Department of Transport of Shaanxi Province and Shaanxi Provincial Highway Bureau for providing crash data.

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