International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 12 Dec 2023, pp: 07-16 www.ijaem.net ISSN: 2395-5252

Temporal Instability of Factors Affecting Injury Severity in Single-Vehicle Crashes on Rural Highways

Yaping Wang, Yuxin Han, Wenjian Zheng,Fulu Wei*
School of Transportation and Vehicle Engineering, Shandong University of Technology, Zibo 255000, Shandong, China.
Corresponding Author: Fulu Wei

Date of Submission: 06-12-2023 Date of Acceptance: 16-12-2023

ABSTRACT: In order to explore the time stability of the factors influencing the severity of single-vehicle crashes in rural areas. Using the five-year single vehicle crash data from 2015 to 2019 in Shandong Province, random parameters Logit model for estimating the crash severity using a random parameter logit model is used to capture the potential unobserved heterogeneity. The likelihood ratio test is conducted to check the overall stability of the model estimation in different time periods, and the marginal effect of each explanatory variable is considered to investigate the time stability of the impact of parameter estimation on the probability of crash severity. The results show that the driver's gender, age(≤25), whether to use seat belts / helmets, and non-dry road surface have little difference in the five-year crash modeling, and are basically stable. In addition, the analysis of individual marginal effects of specific variables shows that there are great differences with the passage of time. The research results can provide theoretical support for effectively reducing the severity of single-vehicle crashes in rural areas and improving the level of rural traffic safety.

KEYWORDS: Traffic engineering, Crash severity, Random parameter logit model, Rural single-vehicle crashes.

I. INTRODUCTION

In 2020, road traffic crashes decreased significantly, with 1.66 deaths per 10,000 vehicles in road traffic crashes, down 7.8%. However, the total number of road traffic crashes and the number of large-scale traffic crashes still account for about 77% and 60% of the total number of various types of production safety crashes in the country, and according to statistics, road traffic crashes on rural roads account for about 41.06% of the total number of traffic crashes each year [1], and on the whole the road safety situation has not yet been fundamentally improved, especially road safety in rural areas is in urgent need of strengthening.

Previous studies have found that among all crash types, single-vehicle crashes have a high fatality rate, with the number of fatalities climbing year by year, and their probability of fatal crashes is 2.08 times higher than that of multi-vehicle crashes [2]. Single-vehicle crashes have a particularly significant impact on rural road traffic safety. The average annual growth rates of fatal crashes and the number of fatalities were 3.08% and 3.19%, respectively, in single-vehicle crashes on rural roads from 2015 to 2019 [3]. So far, the high lethality characteristics of rural road single-vehicle crashes have received extensive attention and research from traffic safety experts.

In order to mitigate the damage caused by rural road traffic crashes and form effective safety countermeasures, scholars have carried out extensive research and conducted a series of qualitative and quantitative analyses of rural road traffic crash data, and explored the quantitative relationship between the influencing factors and the severity of the rural road traffic crashes [4]. The existing studies have found that certain factors have a significant effect on both urban and rural road single-vehicle crashes, and certain factors have a significant effect on only one type of single-vehicle crashes, for example, segregation, time of crash (18:00-23:59), etc. have a significant effect only on urban single-vehicle crashes, while male drivers, sloping roads, etc. have a significant effect only on rural single-vehicle crashes and rural roads are more prone to serious crashes than urban roads [5].

Domestic and international scholars have conducted extensive investigations on the severity of single-vehicle crashes to quantify the degree of influence of factors on the severity of crashes. The influence of various influencing factors on road traffic crashes may not have a constant effect [6], and the influence of various factors on the severity of road traffic crash injuries may vary over time. Yu [7] analyzed the North Carolina 2014-2017 crash data for modeling analysis and found that the effects of factors such as alcohol, passenger cars, pickup trucks, wet road conditions, snow and ice conditions, and curved roads were relatively stable over time, while factors such as speed limit (35-55mph), urban areas, and median width differentially affected the severity of driver injuries.

The severity of driver injuries in traffic crashes has discrete characteristics, and to accommodate this unique nature, several discrete statistical models have been introduced to quantify the associations between crash injury severity and various risk factors. Abrari Vajari [8] considered driver, intersection, collision, and environmental factors, and developed a multinomial logit model using motorcycle crash data from Australia to explore the motorcycle crash severity and influencing factor relationships. However, the multinomial logit model has the limitation of Independence of Irrelevant Alternatives (IIA), which assumes that disturbances between different types of crashes are independent of each other and do not always exist in real situations. To address the limitations of the IIA, some researchers have proposed the use of a nested Logit model to analyze the influences of other crash types. The essence of nested Logit models is that by nesting multiple layers of Logit models together, they usually have a better goodness-of-fit than multinomial Logit models. However, the traditional Logit model assumes that there is no variability among sample individuals, i.e., the effect of the variables in the model on the dependent variable is fixed. In order to solve the limitation that the multinomial logit model fails to take into account the variability of individuals with the IIA assumptions, the random parameters Logit model was Constructed [9], and Yu [10] et al. based on the random parameters Logit model investigated the heterogeneity of factors affecting driver injury severity in snow-related rural single-vehicle based on a random parameter Logit model.

Therefore, in order to investigate the temporal stability of factors in rural single-vehicle crashes, this paper constructs a random parameter Logit model using crash data from Shandong Province and considers the marginal effects of explanatory variables over time in order to investigate the potential temporal variation in the effect of individual parameter estimates on the probability of injury severity.

II. DATA DESCRIPTION

Based on the road traffic crash database of a province in China, a total of 10,890 single-vehicle crashes from 2015 to 2019 were screened; crash data with incomplete information were excluded. In total, 10,600 single-vehicle crashes on rural roads were selected as the research object, including 2080 crashes in 2015, 2102 crashes in 2016, 2064 crashes in 2017, 2087 crashes in 2018, and 2267 crashes in 2019. Based on the severity of driver injury, the severity of the crashes was divided into three categories-no injury(NI), minor injury(MI), and severe injury/death(SF). Injury severity was taken as the dependent variable of the model.

Several potential influencing factors of these crashes were selected and analyzed from four aspects—driver, vehicle, road, and environment, specifically including driver gender, driver age, seatbelt/helmet, vehicle type, road surface, intersection/road, road type, weather conditions, and visibility. For road surface, ice–snow and wet road surfaces were combined as non-dry roads and were divided into dry and non-dry in the modeling process. As the proportion of agricultural machinery vehicles and buses account for less than 1 percent of vehicles, they were combined in subsequent modeling. Descriptive statistics of the variables are shown in Table 1, and the trend of traffic crash injury severity is shown in Figure 1.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 12 Dec 2023, pp: 07-16 www.ijaem.net ISSN: 2395-5252

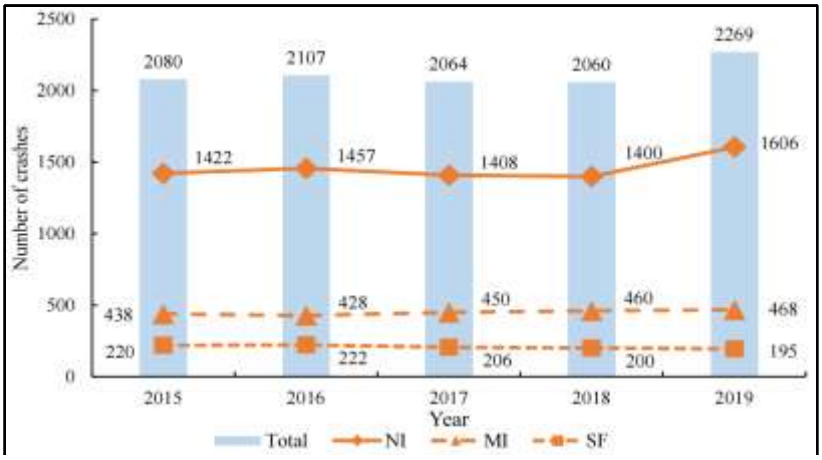

Figure 1. Trend of traffic crash injury severity

Table 1 Descriptive statistics of explanatory variables

VARIABLE	2015	2016	2017	2018	2019
	NUMBER (PERCENTAGE)	NUMBER (PERCENTAGE)	NUMBER (PERCENTAGE)	NUMBER (PERCENTAGE)	NUMBER (PERCENTAGE)
Driver gender					
Female *	186（8.94%）	191（9.07%）	216（10.47%）	258（12.52%）	286（12.4%）
Male	1894（91.06%）	1916（90.93%）	1748（84.69%）	1802（87.48%）	2083（87.6%）
Driver age					
≤25	456（21.92%）	442（20.98%）	489（23.68%）	427（20.73%）	432（20.53%）
26–55 *	1413（67.93%）	1399（66.39%）	1352（65.5%）	1466（71.17%）	1728（71.44%）
>55	211（10.15%）	266（12.61%）	223（10.7%）	167（8.10%）	109（8.03%）
Seatbelt/ helmet					
Used*	1644（79.04%）	1673（79.4%）	1601（77.57%）	1546（75.05%）	1873（75.29%）
No used	436（20.96%）	434（20.6%）	463（22.43%）	514（24.95%）	396（24.71%）
Vehicle type					
passenger car*	1097（52.74%）	982（46.61%）	1124（54.45%）	1302（63.08%）	1236（54.47%）
Motorcycle	568（27.31%）	597（28.33%）	496（24.03%）	433（20.97%）	497（21.90%）
Truck	395（18.99%）	512（24.3%）	422（20.45%）	309（14.97%）	515（22.70%）
Other	20（0.96%）	16（0.76%）	22（1.07%）	16（0.78%）	21（0.93%）
Road surface					
Dry*	1719（82.64%）	1643（77.98%）	1577（76.41%）	1478（71.75%）	1570（72.02%）
Non-dry	361（17.36%）	464（22.02%）	487（23.59%）	582（28.25%）	699（27.98%）
Intersection/section					
section	1294（62.21%）	1370（65.02%）	1307（63.32%）	1158（56.21%）	1289（56.63%）
Intersection *	786（37.79%）	737（34.98%）	757（36.68%）	902（43.79%）	980（43.37%）
Weather					

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 12 Dec 2023, pp: 07-16 www.ijaem.net ISSN: 2395-5252

VARIABLE	2015	2016	2017	2018	2019
	NUMBER (PERCENTAGE)	NUMBER (PERCENTAGE)	NUMBER (PERCENTAGE)	NUMBER (PERCENTAGE)	NUMBER (PERCENTAGE)
clear*	1410（67.79%）	1655（78.55%）	1641（79.51%）	1387（67.33%）	1383（60.95%）
Non-clear	670（32.21%）	452（21.45%）	423（20.49%）	673（32.67%）	886（39.05）
Visibility					
<100m	321（15.43%）	277（13.15%）	326（15.79%）	249（12.09%）	253（11.15%）
100–200m	600（28.85%）	740（35.12%）	671（32.51%）	709（34.42%）	742（32.70%）
>200m*	1159（55.72%）	1090（51.73%）	1067（51.7%）	1102（53.49%）	1274（53.15%）

III. METHODOLOGY

THE RANDOM PARAMETER LOGIT MODEL

The multinomial logit model (MNL) is the basis of the discrete model system; it is widely used in the field of transportation due to its simple form, small size requirements, and easy solution [11]. The construction of MNL needs to introduce the utility function, as shown in Eq. (1):

$$T_{ij} = \beta_i X_{ij} + \varepsilon_{ij} (i = 1\ldots n; j = 1\ldots J) \quad (1)$$

where T_{ij} is the utility function of the injury severity j in the ith crash; X_{ij} is the vector of the explaining variables (driver, vehicle, road, environment, etc.); β_i is the coefficient of the independent variable; ε_{ij} is the disturbance term observed in the utility function.

With the assumption of the extreme-value distributed ε_{ij}, the standard multinomial logit model is specified as shown in Eq. (2):

$$P_{ij} = \frac{\exp(\beta_i X_{ij})}{\sum_{i=1}^{I} \exp(\beta_i X_{ij})} \quad (2)$$

where J is the classification set of the severity of crashes. In this paper, the severity of crashes is divided into no injury, minor injury and severe injury/death, and J values are 1, 2, 3.

MNL must consider the limitation of IIA, and the parameters of the model are fixed values, which cannot reflect the heterogeneity of variables (Sun et al. 2022). In the process of modeling, adding a random iterm to the parameter can reflect the random change of the influence of this factor on crash severity. Then, a random parameter logit model(RPL) can be built that takes into account the heterogeneity between different individuals[12].

To explain the unobserved heterogeneity, a random term is added to β_j, which can be expressed as a linear combination of the estimated mean value of the parameters and the correlated random error term:

$$\beta_{ij} = \beta_j + \Gamma_j v_{ij} \quad (3)$$

where, β_j is the estimated value of the average parameter in crashes; Γ_j is the coefficient matrix of random parameters and represents the correlation of random errors between coefficients, and v_{ij} is the random term with mean value of 0 and the covariance matrix of the identity matrix.

The regression function of RPL is shown in Eq. (4):

$$P_{ij} = \frac{\exp\left[\left(\beta_j + \Gamma_j v_{ij}\right) X_i\right]}{\sum_{j \in J} \exp\left[\left(\beta_j + \Gamma_j v_{ij}\right) X_i\right]} \quad (4)$$

Due to the uncertainty of the probability density function of RPL has no fixed integral form. Therefore, the maximum likelihood method based on simulation was adopted for parameter estimation, which balances the computational efficiency and goodness of fit. The Halton sampling method was used in this study with 1,000 sampling times. Before parameter estimation, distribution forms of probability density function of parameters should be specified. The four common distribution forms are normal, lognormal, trigonometric, and uniform. According to previous studies, normal distribution is usually the most suitable data to describe road traffic crash severity [13].

MARGINAL EFFECTS

The regression parameters obtained by RPL can reflect the influence trend only of influencing factors on crash severity and cannot effectively measure the influence degree of crash severity. Therefore, on the basis of estimating the parameters of the model, it is also necessary to calculate the marginal effect value of the significant influencing factors. The calculation formula of the marginal effects is shown in Eq. (5):

$$E_{x_{ijk}}^{P_{ij}} = \frac{1}{N} \sum_{i=1}^{N} (P_i(\mathrm{j} | x_{ijk} = 1) - P_i(\mathrm{j} | x_{ijk} = 0)) \quad (5)$$

where, when other variables remain unchanged when x_{ijk} =1, $P_i(j|x_{ijk}=1)$ is the probability of the occurrence of the ith crash with severity j; when other variables remain unchanged when x_{ijk} =0, $P_i(j|x_{ijk}=0)$ is the ith crash with severity j; x_{ijk} is the value of the k independent variable in the ith crash whose severity is j.

MODEL DIAGNOSTICS

After the parameter estimation of the model, it is necessary to evaluate the goodness of fit. The goodness of fit index McFadden Pseudo R^2 is a relative value; the larger the value of McFadden Pseudo R^2, the better the goodness of fit. When the value of McFadden Pseudo R^2 is between 0.2 and 0.4, the model can be fitted well. The calculation formula of McFadden Pseudo R^2 is shown in Eq. (6):

$$McFadden\ Pseudo\ R^2 = 1 - \frac{LL(\beta)}{LL(0)} \quad (6)$$

where, LL(β) is the logarithmic likelihood convergence value of the model and LL(0) is the initial logarithmic likelihood value.

TRANSFERABILITY TESTS

A series of tests are first performed to explore the temporal stability of explanatory variables in two consecutive years,

$$x^2 = -2\left[LL\left(\beta_{t_2t_1}\right) - LL\left(\beta_{t_1}\right)\right] \quad (7)$$

where t_1 and t_2 denote two different time-periods periods. $LL\left(\beta_{t_2t_1}\right)$ represents the log-likelihood at the coverage of the model that use crash data from t_1, while containing significant indicators during t_2; $LL\left(\beta_{t_1}\right)$ is the log-likelihood at the coverage of the injury-severity model containing explanatory variables using data during time-period t_1 ,with the same factors but with parameters no longer restricted to the covered parameters of t_2 . The likelihood test is also reversed: t_1 is replaced with t_2 , and t_2 replaces time-period t_1 .

The χ^2 is χ^2 distributed, which is used to determine the null hypothesis that the parameters are the same between t_1 and t_2 can be rejected or accepted. Table 2 presents the likelihood ratio tests using Eq. (7) for RPL. Table 2 shows that among the tests, all the tests produce a confidence level that is greater than 99%, indicating the null hypothesis is rejected. The testing results in Table 2 demonstrate the temporal instability in determinants among the selected time-periods (i.e., 2015, 2016, 2017, 2018, and2019).

Table 2 Likelihood ratio test results between different time periods

t_1	t_2				
	2015	2016	2017	2018	2019
2015	-	249.018（22）[>99.99%]	106.474（16）[>99.99%]	128.406（16）[>99.99%]	118.548（18）[>99.99%]
2016	108.334（21）[>99.99%]	-	77.540（16）[>99.99%]	46.702（16）[>99.99%]	57.467（18）[>99.99%]
2017	212.822（21）[89.97%]	219.952（22）[>99.99%]	-	168.350（16）[>99.99%]	158.376（18）[>99.99%]
2018	107.992（21）[>99.99%]	216.750（22）[>99.99%]	86.434（16）[>99.99%]	-	78.076（18）[99.99%]
2019	164.476（21）[73.99%]	247.054（22）[>99.99%]	122.696（16）[>99.99%]	116.746（16）[>99.99%]	-

Note: χ^2 values with degrees of freedom in parenthesis and confidence level in brackets

IV. RESULTS

We examined how the effects of individual explanatory variables change over time. This was done by tracking the marginal effects over time of the variables discussed below.

Table 3 Model estimation results

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 12 Dec 2023, pp: 07-16 www.ijaem.net ISSN: 2395-5252

VARIABLES	2015 Coefficient （z-stat）	2016 Coefficient （z-stat）	2017 Coefficient （z-stat）	2018 Coefficient （z-stat）	2019 Coefficient （z-stat）
[MI] Constant	1.138(2.87)	0.937(1.69)	2.923(5.89)	3.040(7.18)	1.930(4.89)
[SF] Constant	2.024(4.36)	1.270(3.76)	2.162(4.73)	2.102(5.83)	2.556(7.33)
[MI] gender(Male)	0.461(2.63)	0.359(2.48)	0.317(2.48)	0.243(2.75)	0.364(2.19)
[SF] gender(Male)	0.709(3.49)	0.179(1.56)	0.622(4.11)	0.412(3.12)	0.472(3.27)
[MI]age(≤25)	0.618(3.55)	0.441(1.96)	0.457(3.02)	-	0.526(3.35)
Standard deviation	0.973(1.59)	-	0.713(3.49)	-	-
[SF] age(≤25)	0.374(2.17)	0.497(2.21)	0.624(5.23)	0.457(4.56)	0.713(5.58)
Standard deviation	0.742(2.41)	0.689(2.68)	-	-	-
[MI] age(>55)	-	0.593(2.34)	0.315(2.72)	0.338(3.04)	0.417(2.71)
[SF] age(>55)	0.860(4.02)	-	-	-	-
[SF] Seatbelt/helmet (No used)	1.023(6.79)	0.872(3.12)	0.843(4.63)	0.782(4.77)	0.828(6.42)
[MI] Motorcycle	0.619(4.82)	0.625(2.55)	0.577(4.42)	0.445(3.12)	0.634(4.85)
Standard deviation	-	1.035(3.97)	-	0.614(3.56)	-
[SF Motorcycle	0.657(5.02)	0.395(1.24)	-	-	0.315(2.78)
[MI] Truck	0.572(3.64)	-	0.627(5.09)	0.612(5.98)	-
[SF] Truck	-	0.612(2.09)	0.339(1.77)	0.413(2.79)	0.592(3.64)
[MI] Non-dry	0.748(3.42)	0.419(1.49)	1.016(6.79)	0.573(2.44)	0.563(3.83)
[SF] Non-dry	0.455(2.47)	0.508(1.64)	0.576(2.52)	0.528(2.12)	0.826(5.34)
Standard deviation	-	-	-	0.832(2.32)	1.242(3.98)
[MI] section	0.337(2.99)	0.552(2.03)	-	0.615(4.06)	0.427(2.99)
[SF] section	-	0.357(1.96)	-	-	-
[MI] Non-Clear Weather	0.634(3.04)	0.813(3.11)	0.512(3.64)	-	0.499(6.33)
[SF] Non-Clear Weather	0.815(4.62)	0.615(2.89)	-	-	-
[MI] Visibility (<100m)	0.723(4.79)	0.258(1.46)	-	0.562(4.51)	-
[SF] Visibility (<100m)	0.582(2.56)	0.451(3.37)	-	-	0.683(4.52)
[MI] Visibility (100-200m)	0.536(2.03)	0.331(2.36)	0.365(4.03)	-	-
[SF] Visibility (100-200m)	-	-		-	0.474(2.96)
Log-likelihood at zero, LL(0)	-2203.145	-2319.181	-2178.572	-2245.284	-2563.891
Log-likelihood at convergence, LL(β)	-2004.442	-2079.332	-1932.493	-2033.893	-2210.160
McFadden Pseudo R-	0.265	0.238	0.256	0.307	0.298

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 12 Dec 2023, pp: 07-16 www.ijaem.net ISSN: 2395-5252

Squared					

DRIVER CHARACTERISTICS

The driver variable was found to be a significant factor influencing the severity of driver injuries in all years, as shown in Figure 1, from 2015 to 2019, male drivers had an increased likelihood of minor and serious injuries/fatalities compared to female drivers, with the probability of serious/fatal crashes higher than both higher than the probability of minor crashes, except for 2016.In 2016, male drivers were subject to minor crashes probability was higher than the probability of serious injury/fatal crashes. While the values of the marginal effects indicate that the effect value of this variable varies quite little (the probability of injury varies by up to 0.036), Figure 1 shows that the effect of this variable on the probability of injury is quite stable over time.

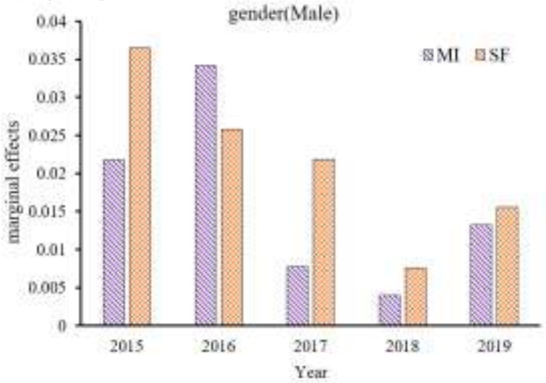

Figure 2. Marginal effects for "male"

Dividing driver age into three categories, with age (26-55) as the reference variable, age (≤25)was significant in all five years of parameter estimation, except in 2015, when the probability of a driver being involved in serious/fatal crashes were higher than that of minor crashes, in 2015, when the probability of being involved in minor crashes was higher than that of being involved in serious/fatal crashes, and in 2018, where there was no significant effect on minor crashes for driver age(≤25). With a few exceptions, the effect of this variable on the probability of injury has been stable over time.

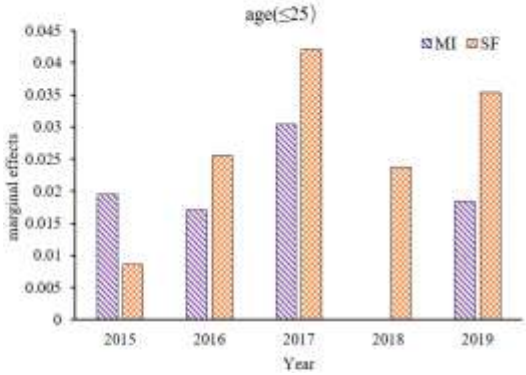

Figure 3 Marginal effects for "age(≤25)"

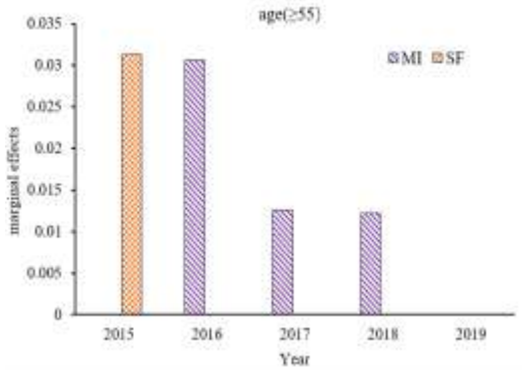

Figure 4 Marginal effects for "age(>55)"

The variable of driver age(>55) does not have a significant effect on crash severity in 2019, and only has a significant effect on serious/fatal crashes in 2015, and a significant effect on minor injury crashes in other years, with a marginal effect value of up to 0.312, and in general, this variable shows an unstable trend over time.

Not using seat belts/helmets was significant in all years, with the use of seat belts/helmets as the reference variable, when crashes occur, seat belts, and helmets provide cushioning, protection, and reduce the probability of driver injuries. This variable is an important factor influencing the severity of driver injuries in all years, and the value of the marginal effect of this variable varies over time, with a small difference in the variation, and in general tends to be stable.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 12 Dec 2023, pp: 07-16 www.ijaem.net ISSN: 2395-5252

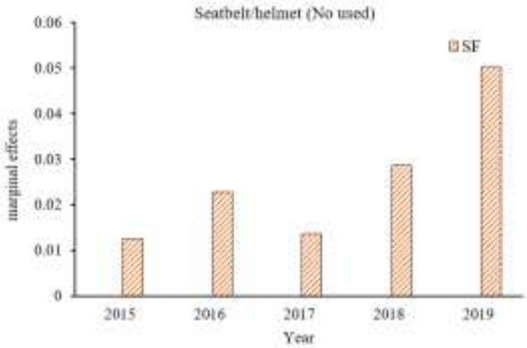

Figure 5 Marginal effects for "Not using seatbelts/helmets"

VEHICLE CHARACTERISTICS

Vehicle types were classified into four categories, classifying both as other vehicle types, and using passenger cars as the reference variable, over a five-year period, motorcyclists were significantly involved in only minor injury crashes in 2017 and 2018, the probability of motorcyclists being involved in minor and serious/fatal crashes increased with a greater probability in 2015 and 2016 compared to the other years. The decrease in the probability of injury after 2016 may be due to the rapid introduction of safety features during this period, driver adaptation to these features, and other factors.

The variable "trucks" increased the probability of minor injury crashes by 2.67% in 2015, and increased the probability of serious/fatal injury crashes by 1.88% in 2016 and 2.30% in 2019, and the variable "trucks" had a higher probability of minor injuries than serious/fatal injuries crashes in both 2017 and 2018, which is not time-stable.

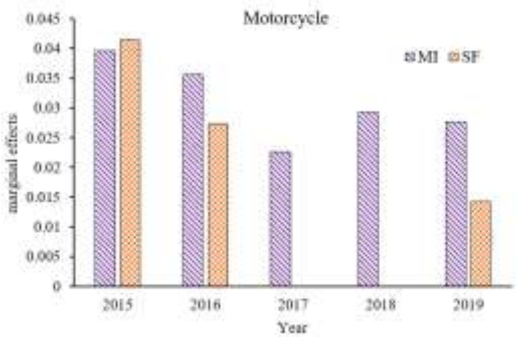

Figure 6 Marginal effects for "Motorcycle"

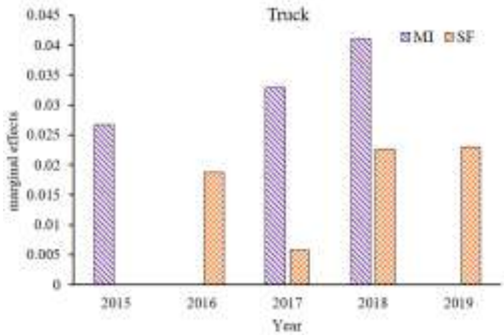

Figure 7 Marginal effects for "Truck"

ROAD CHARACTERISTICS

Road surface condition is also an important factor affecting the severity of driver injuries in all years, the combination of snow, ice, and wet road surfaces into non-dry road surfaces, with dry road surface as the reference variable, under the non-dry road surface, the probability of serious/fatal crashes is higher than that of minor injury crashes in 2016 and 2019, and the probability of minor injury crashes is higher than that of serious/fatal injury crashes in the rest of the years, and the rate of growth of crashes occurred in the highest rate of growth of crashes in 2016, and the repair of the road, maintenance of roads, and strengthening of the warning signs of the road condition during inclement weather slowed down the probability of the increase in the number of crashes after 2016, and this variable of the road surface condition has shown a stable trend in the change over time.

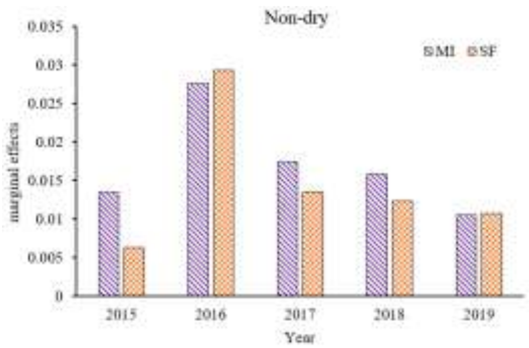

Figure 8 Marginal effects for "non-dry"

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 12 Dec 2023, pp: 07-16 www.ijaem.net ISSN: 2395-5252

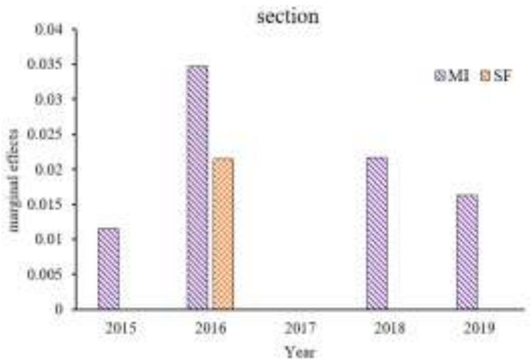

Figure 9 Marginal effects for "section"

The variable of intersection/ section type was not statistically significant in 2017, and using intersection as the reference variable, the variable of section was only associated with minor injury crashes in 2015, 2018 and 2019, and in 2016, the probability of minor injury crashes increased by 3.47% and 2.15%, respectively, as did the probability of serious/fatal crashes, which varies considerably over time and is not have stability.

ENVIRONMENTAL CHARACTERISTICS

Using clear weather as the reference variable, non-clear weather did not have a significant effect on crash severity in 2018, was only associated with minor injury crashes in 2017 and 2019, and non-clear weather was associated with both minor and serious/fatal crashes in 2015 and 2016, with the variable showing a high degree of variability over time, and was not stable over time.

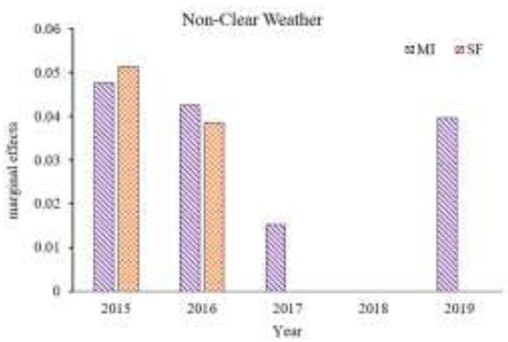

Figure 10 Marginal effects for "non-clear weather"

Visibility was categorized into three categories, below 100m, 100-200m and above 200m, using above 200m as the reference variable, visibility (<100m) had a significant role with minor and serious/fatal crashes in 2015 and 2016 and did not have a significant effect on crash severity in 2017. Visibility (>200m) was significantly related to minor injury crashes in 2015, 2016 and 2017, and significantly related to SF crashes in 2019. Overall, visibility does not have a stabilizing effect over time.

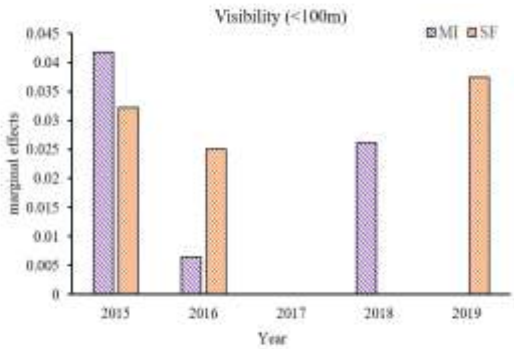

Figure 11 Marginal effects for "visibility (<100m)"

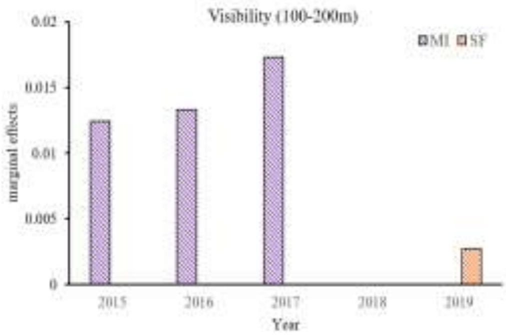

Figure 12 Marginal effects for "Visibility (100-200m)"

V. CONCLUSIONS

Based on a random parameters logit model, the temporal stability of the driver injury severity model was examined using traffic crash data from 2015-2019 in Shandong Province, China. A series of random parameters logit models were estimated for each of the five individual years of the data. The results of the likelihood ratio test showed statistically significant differences in parameter estimates across crash data years. Parameter estimates for models of driver crash severity based on the year of data used were generally not temporally stable, despite some common characteristics of the different years of data. Driver gender, age(≤25), seatbelt/helmet use, and non-dry road condition did not vary too much and were generally stable over the five years of crash modelling.Furthermore, analyses of individual marginal effects for specific variables showed significant differences over time.

VI. ACKNOWLEDGEMENTS

This research was jointly supported by Open Project of Key Laboratory of Road Traffic Safety of the Ministry of Public Security (Grant

No. 2023ZDSYSKFKT14) and University and Urban Integration Development Plan Project of Zhangdian District (Grant No.2022JS002).

VII. DISCLOSURE STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

[1]. Ministry of Transport of the People's Republic of China. Statistical Bulletin on the Development of the Transport Industry in 2021.

[2]. Ministry of Public Security Traffic Management Bureau. Annual Report on Road Traffic Accident Statistics of the People's Republic of China; Ministry of Public Security Traffic Management Bureau: Beijing, China, 2020.

[3]. X. Wang, M. Feng. "The Key Laboratory of Road and. Freeway single and multi-vehicle crash safety analysis: influencing factors and hotspots" in Accident Analysis and Prevention, 132: 105268, 2019.

[4]. F. Wei, Z. Cai, Z. Yan, P. Li, Y. Qing, L. Chen, "Analysis of the incidence of death accidents based on Bayesian Logit model" in Journal of Guangxi University (Natural Science Edition), 46(4): 1054-1062, 2021.

[5]. C. Se, T. Champahom, S. Jomnonkwao, P. Chaimuang, V.Ratanavaraha, "Empirical comparison of the effects of urban and rural crashes on motorcyclist injury severities: A correlated random parameters ordered probit approach with heterogeneity in means" in Accident Analysis & Prevention, 161: 106352, 2021.

[6]. F. Bella, A. Calvi, F. D'Amico, "Analysis of driver speeds under night driving conditions using a driving simulator" in Journal of Safety Research, 49(45): el–52, 2014.

[7]. M. Yu, C. Zheng, C. Ma, J. Shen, "The temporal stability of factors affecting driver-injury severity in run-off-road crashes: A random parameters ordered probit model with heterogeneity in the means approach" in Accident Analysis & Prevention, 144, 105677, 2020.

[8]. M. A. Vajari, K. Aghabayk, M. Sadeghian, N.Shiwakoti, "A multinomial logit model of motorcycle crash severity at australian intersections" in Journal of Safety Research, 73, 17–24, 2020.

[9]. A. Behnood, F.Mannering, "Time-of-day variations and temporal instability of factors affecting injury severities in large-truck crashes" in Analytic Methods in Accident Research, 23, 100102, 2019.

[10]. H. Yu, R. Yuan, Z. Li, G. Hui, D. Ma, "Identifying heterogeneous factors for driver injury severity variations in snow-related rural single-vehicle crashes" in Accident Analysis & Prevention, 144: 105587, 2020.

[11]. Z. Ma, Y. zhang, Y. Yang, X. Tan, "Research on models for predicting severity of traffic accident in highway tunnel" in China Safety Science Journal, 25(5): 75-79, 2015.

[12]. M. Pour-Rouholamin, H. Zhou, "Investigating the risk factors associated with pedestrian injury severity in Illinois" in Journal of Safety Research, 57: 9-17, 2016.

[13]. C. Se, T. Champahom, S. Jomnonkwao, A. Karoonsoontawong, V. Ratanavaraha, "Temporal stability of factors influencing driver-injury severities in single-vehicle crashes: A correlated random parameters with heterogeneity in means and variances approach" in Analytic Methods in Accident Research, 32: 100179, 2021.