sustainability

Article

Quarterly Instability Analysis of Injury Severities in Truck Crashes

Fulu Wei [1], Danping Dong [1], Pan Liu [2], Yongqing Guo [1,*], Zhenyu Wang [3] and Qingyin Li [1]

1 School of Transportation and Vehicle Engineering, Shandong University of Technology, Zibo 255000, China
2 School of Transportation, Southeast University, Nanjing 211102, China
3 Center for Urban Transportation Research, University of South Florida, Tampa, FL 33620, USA
* Correspondence: yongqing.guo@sdut.edu.cn

Abstract: The impact of trucks on road traffic safety has been extensively studied, but the factors influencing truck crash injury severity have not yet been examined from the quarterly perspective. Crash data for Shandong Province in China for 10 years (2012–2021) were reviewed to investigate the transferability of the determinants of the severity of truck crash injuries in four quarters. Three injury severity levels were considered and a random parameters logit model (RPL) considering the heterogeneity of means and variances was constructed to assess the factors affecting the severity of crash injury. The significant variables were explored from the influencing factors of driver, vehicle, crash type, road, environment, and temporal characteristics. A likelihood ratio test was employed to assess the transferability of the crash model over four quarters, and we used marginal effects to analyze the stability of the influencing factors. The results indicated that there was instability among the four quarterly variables that had to be modeled separately. There were also some variables, such as heavy vehicle and multiple-vehicle crashes, that simultaneously affected the severity of truck crash injuries across the four quarters, but the degree of impact was different. The results could enable engineers and policy makers to better formulate management rules and propose appropriate measures according to quarterly changes.

Keywords: truck crash severity; random parameters logit model; heterogeneity; temporal stability; transferability

Citation: Wei, F.; Dong, D.; Liu, P.; Guo, Y.; Wang, Z.; Li, Q. Quarterly Instability Analysis of Injury Severities in Truck Crashes. *Sustainability* **2022**, *14*, 14055. https://doi.org/10.3390/su142114055

Academic Editors: Juneyoung Park, Yina Wu and Hochul Park

Received: 11 September 2022
Accepted: 25 October 2022
Published: 28 October 2022

1. Introduction

Truck transport plays a vital role in social and economic development. According to 2021 data from the Ministry of Transport of the People's Republic of China [1], by the end of 2021, the number of trucks in China was 11.7326 million, and the tonnage of trucks reached 170.995 million tons, with increases of 5.7% and 8.3%, respectively, compared with the same period in 2020. Trucks, as the main mode of transportation of goods, transport about 74.76% of the goods in China [2]. Although trucks have unique advantages in transporting goods, they are prone to traffic crashes due to their large volume, long body, long braking distance, and high violation rate [3], resulting in serious safety problems for road traffic. According to the traffic crash data released by the Traffic Administration of the Ministry of Public Security of China in 2019, a total of 12,473,000 road accidents occurred, which included 62,763 deaths. Among them, deaths caused by truck traffic accidents accounted for 31.68% of the total road traffic accidents [4]. The fatality rate of truck crashes in China was 34%, accounting for 55% of the national road traffic crashes fatality rate in the same period [5]. According to the statistics of the Federal Motor Carrier Safety Administration (FMCSA), in 2017, the annual average number of heavy truck traffic accidents in the United States reached 475,001, including 5360 deaths and 142,000 injuries. Moreover, truck crashes accounted for 7.36% of the total traffic accidents, while fatalities accounted for 13.4% of the total traffic accidents [6]. The UK STATS19 accident database shows that truck crashes accounted for 13% of the total number of accidents, while deaths accounted for 26% of the total fatalities, nearly twice the rate of truck crashes from 2015 to 2018. Therefore, it could be concluded that truck crashes generally cause more casualties and property losses than other types of vehicle crashes, posing a significant threat to public security.

Behnood [3] discussed the differential impact on truck injury severity across the time of day and year and found that the influencing factors were unstable across the time of day and year. They also investigated the transferability of the severity of truck collision injury between weekdays and weekends, and the results showed that it was necessary to model weekdays and weekends separately, because the influence factors for each model varied [7]. Although many studies analyzed truck crash injury severity and its influencing factors [3,8,9], there remains a lack of research on the seasonal instability of factors. This study considered the possibility that the influencing factors that determine the severity of truck crash injuries may vary from quarter to quarter.

The instability of quarterly factors on the severity of truck crash injuries is considered primarily from two aspects. First, companies set targets according to quarterly uploading statements; the objectives and products completed in each quarter are different, and the truck transportation industry adjusts transportation routes and times accordingly. Second, the instability of quarterly impact on truck crashes is related to weather, holidays, and other factors. Based on these two points, quarterly variations may play an important role in influencing the severity of traffic injuries. This study considered the possibility that the impact of the variables that determine the severity of truck crash injury may vary by quarter rather than the simple probabilistic variation caused by the use of indicator variables.

The primary contents of this study are organized as follows: (1) factors affecting the severity of truck collision injury are analyzed; (2) the relevant data are described in detail; (3) an analysis method of the factors influencing the severity of truck crash injury is proposed, and the transferability of the model is tested; (4) the estimation results of the model are discussed, and a summary and conclusion are presented.

2. Literature Review

In the process of reviewing the literature, several factors were identified that might influence the severity of truck crash injuries. Depending on the attributes of the factors, they can be classified into five main categories—driver, vehicle, crash type, road, environment, and time. Driver factors can be divided into age, gender, driving fatigue, and drunk driving. In a study by Chen [10], it was noted that drivers aged 50 and over had an increased probability of being seriously injured in single-vehicle crashes involving a truck, but the probability decreased in multi-vehicle crashes. Drivers aged 25 and under had a decreased probability of being seriously injured in single-vehicle truck crashes, and the probability of no and minor injuries increased. Zheng [11] noted that younger drivers (under the age of 25) had a greater probability of fatalities, but a study by Behnood [3] found that drivers under the age of 31 had a greater probability of less serious injuries. Gender also had a complex effect on the severity of truck crash injuries. Chen [10] showed that female drivers were more likely to be injured/killed regardless of the type of crash, whereas some studies showed that male drivers were more likely to be seriously injured/killed and less likely to have no injuries in a crash relative to female drivers [12]. Behnood [7] also demonstrated that male drivers were less likely to suffer minor injuries and more likely to have no or serious injuries in weekday crashes. In reality, the number of male truck drivers is much greater than that of female drivers, which may have affected the crash analysis results due to the insufficient sample size of female drivers.

Driver fatigue was also an important factor in the severity of driver crash injuries. If a truck driver was involved in a multi-vehicle crash during fatigued driving, serious injuries occurred, but in a single-vehicle crash, the degree of injury was lower [10]. For crashes involving drunk driving, Behnood [7] found that such crashes were less likely to cause minor and serious injuries if they occurred during a weekday; this variable was not significant on weekends. However, Wang [13] found that drunk driving led to an increase in the probability of traffic crash injuries and fatalities.

An analysis was conducted of the effect of vehicle attribute variables on crashes. Single-unit trucks had a higher probability of disabling/fatal injuries in multi-vehicle crashes than multi-unit trucks [12]. However, the opposite was true in single-vehicle crashes; commercial transport trucks resulted in a reduced probability of crash injuries and fatalities [13], and tankers, flatbeds, and grain trucks resulted in increased crash injury severity [11]. Heavy trucks increased the probability of traffic crashes, and truck loading conditions were significantly associated with severe injury/fatal traffic crashes [14].

With regard to crash characteristics, many researchers found that different vehicle travel status and crash types could lead to distinct crash severity levels. In truck crashes, an increase in the number of vehicles involved increased the likelihood of injury [11]; side collisions and rear-end collisions [3,7] increased the likelihood of minor injuries, and during a working day, trucks turning left or right before a collision could lead to more severe crashes [3].

In terms of various traffic control methods, diverse outcomes of traffic crashes were generally attributed to the presence or absence of a median and the location of collision. Truck violations of traffic signs and signals led to more severe crashes [3]. In multi-vehicle truck crashes, roads with wide lanes, wide medians, and unprotected medians effectively reduced the probability of moderate injuries but increased the probability of serious injuries and fatalities [10]. Concrete medians increased the likelihood of serious/fatal injuries [15]. The likelihood of injuries and fatalities increased for trucks in one-way crashes when the crash location was a sharp turn [10], and the risk of truck crashes was higher on steep downhill sections than on other roadways [16].

Additionally, the climatic factor, the road surface condition, the lighting condition, and the visibility also exerted an influence on the severity. Zheng [11] found that fatal road crashes were less likely to occur in snowy or rainy weather and that bad weather increased the probability of injury/non-disabling injury in single-vehicle truck crashes [10]. Zheng [11] also found that fatal crashes were less likely to occur in snowy or rainy weather and that good weather increased the probability of fatal crashes; cloudy conditions led to a higher probability of minor and serious injury crash outcomes [14]. In terms of road surface condition factors, the probability of both minor and fatal crashes was reduced on icy roads [10] but increased the risk of single fatal crashes and reduced the likelihood of multiple crashes; wet and dry roads increased the probability of fatal injuries [13]. No lighting at night increased the risk of fatal crashes [10,13], and good visibility reduced the severity of injuries in traffic crashes, whereas poor visibility increased the probability of fatal crashes. Crashes during peak hours were more likely to result in more severe injuries to truck drivers than crashes during off-peak hours, with the morning peak showing more incidents for truck drivers [17,18]. A higher proportion of serious injury crashes occurred on weekends than on weekdays [19].

The comparison of existing studies showed that some factors had similar effects on the severity of truck crash injuries, but other factors had opposite effects in different studies. This variability may have been due to the existence of temporal instability or the presence of unobserved heterogeneity of the data as well as differences in modeling methods and inadequate data samples.

3. Data Preparation

This study used the data of truck crashes in Shandong Province from January 2012 to December 2021. The database contained a total of 5062 truck crashes; the trucks included minivans and light, medium, and heavy trucks. The dataset covered five types of crash information, including driver, vehicle, road, environment, and temporal characteristics. The most seriously injured person in the crash was selected as the research object. Three levels of injury were recorded in the dataset—no injury (property damage only), damage injury, and fatal injury. The data were divided by seasonal quarters—the first quarter

(January–March), the second quarter (April–June), the third quarter (July–September), and the fourth quarter (October–December). The frequency (percentage) distribution of each crash injury severity divided by quarter is shown in Table 1. It can be seen that the frequency of crashes in the first quarter was the lowest, at only 18.53%. In comparison, the frequency of crashes in the fourth quarter was the highest, at 28.63%. This indicated that there was temporal instability among quarters, suggesting that the factors that led to the severity of injury changed by quarter.

Table 1. Frequency (percentage) distribution of crash injury severity level by quarter.

Quarter	No Injury (Percentage)	Damage Injury (Percentage)	Fatal Injury (Percentage)	Total
First quarter (%)	27 (2.88)	538 (57.36)	373 (39.77)	938
Second quarter (%)	35 (2.56)	787 (57.49)	547 (39.96)	1369
Third quarter (%)	18 (1.38)	737 (56.43)	551 (42.19)	1306
Fourth quarter (%)	40 (2.76)	803 (55.42)	606 (41.82)	1449
Total (%)	120 (2.37)	2865 (56.60)	2077 (41.03)	5062 (100)

In this study, the model was estimated using NLOGIT5. To avoid bias in the estimation of the model caused by the high correlations among the respective variables and reduce prediction accuracy, a Pearson correlation test [20] was chosen to estimate the correlation coefficient of each pair of variables to ensure the selection of the optimal variables. If the absolute value of the Pearson correlation coefficient was less than 0.3, the two variables were considered not to be significantly correlated. Otherwise, the two variables were considered to be highly correlated, and only one of the variables was selected for inclusion in the regression model during estimation. The selection of model variables was an incremental process. When selecting, it was necessary to add highly-correlated variables to the model to compare the corresponding model fitting indicators and retain the optimal independent variables.

The Pearson correlation test was used to find the optimal variable by running a stepwise regression test on the 20 factors in each quarter. The combination of variables used for quarterly modeling was determined. Taking the first quarter as an example, the correlation among the following variables can be seen from Figure 1: driver driving experience and driver age; vehicle travel status and crash position; crash type, lightening condition, visibility, and crash time; crash position and traffic control mode; junction section type and physical separation of roads; road line type and truck type; road surface condition and weather. Thus, in order to build an excellent model, it was necessary to select a set of variables from them and incorporate them into the model. Similarly, the Pearson correlation test was used to identify highly correlated factors in other quarters. The suitable variables were determined using stepwise regression. Finally, in the modeling process, 12 factors were selected for the first quarter, 11 factors for the second quarter, 12 factors for the third quarter, and 11 factors for the fourth quarter.

Table 2 shows the variables selected in the model and the statistical description of various data (bold italics are the variables that were eventually brought into the model through the Pearson correlation test in the four quarters). It can be seen that most variables had approximately the same mean value across the four quarters. However, some variables also showed different variations. The highest proportion of truck crashes occurred in the driver age ranges of 11–21 and 31–51. Compared with other types of vehicles, heavy trucks had the largest proportion of crashes. In the second quarter, heavy trucks had the largest proportion of collisions, and the average number of traffic accidents occurring when trucks were turning right or left was higher than in other quarters. The probability of side collisions in the second quarter was higher than that in other quarters, and rear-end collisions occurred more frequently in the first quarter.

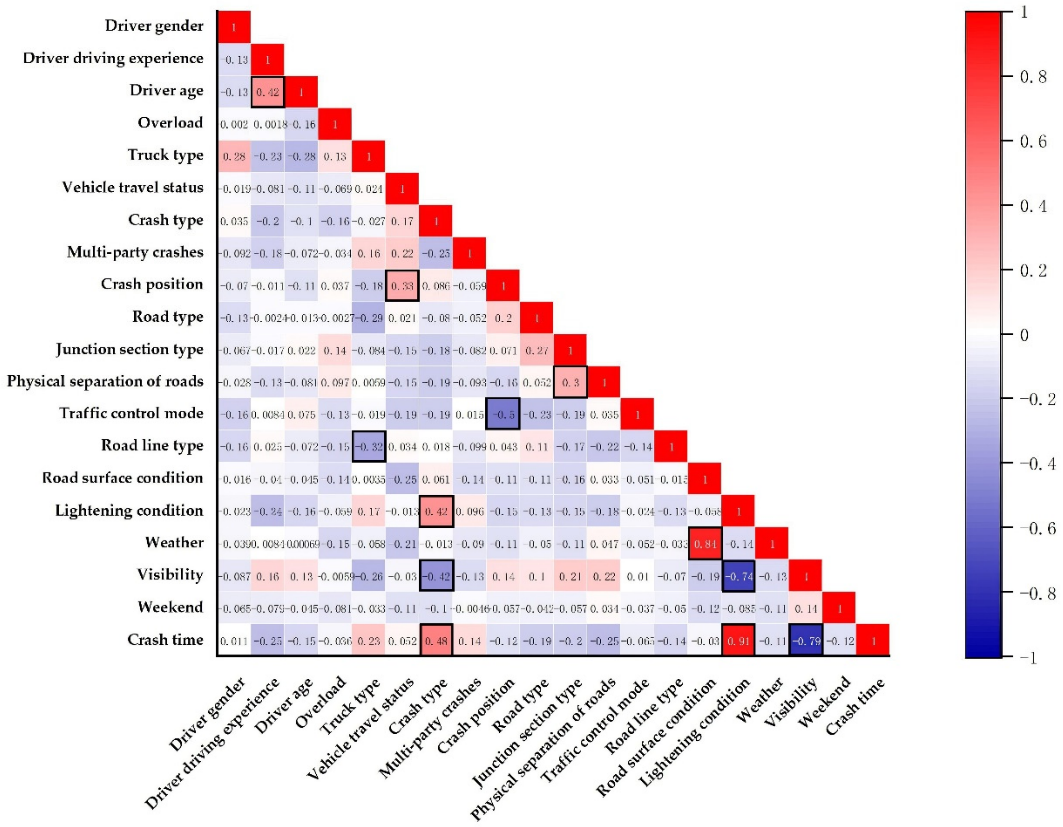

Figure 1. Pearson correlation coefficient test for first quarter.

Table 2. Descriptive statistics of variables.

Variables	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
Driver characteristics				
Driver gender				
1 if male; 0 otherwise	***0.990 (0.098)***	***0.994 (0.076)***	***0.992 (0.091)***	***0.990 (0.101)***
Driver driving experience				
1 if driving experience <11 years; 0 otherwise	0.360 (0.480)	***0.358 (0.480)***	***0.353 (0.478)***	***0.368 (0.482)***
1 if driving experience 11–21 years; 0 otherwise	0.461 (0.499)	***0.443 (0.497)***	***0.432 (0.496)***	***0.451 (0.498)***
1 if driving experience ≥21 years; 0 otherwise	0.179 (0.384)	***0.199 (0.399)***	***0.215 (0.411)***	***0.181 (0.385)***
Driver age				
1 if age < 31; 0 otherwise	***0.128 (0.334)***	0.134 (0.341)	0.136 (0.342)	0.139 (0.346)
1 if age 31–50; 0 otherwise	***0.776 (0.417)***	0.743 (0.437)	0.739 (0.439)	0.734 (0.442)
1 if age ≥ 51; 0 otherwise	***0.096 (0.295)***	0.123 (0.328)	0.126 (0.331)	0.127 (0.333)
Vehicle characteristics				
Overload				
1 if overload; 0 otherwise	***0.036 (0.187)***	***0.028 (0.166)***	***0.028 (0.166)***	***0.028 (0.164)***
Truck type				
1 if micro; 0 otherwise	***0.005 (0.073)***	***0.002 (0.047)***	***0.004 (0.062)***	***0.005 (0.069)***
1 if light; 0 otherwise	***0.277 (0.448)***	***0.245 (0.431)***	***0.263 (0.440)***	***0.283 (0.451)***
1 if medium; 0 otherwise	***0.031 (0.173)***	***0.030 (0.171)***	***0.047 (0.211)***	***0.035 (0.184)***
1 if heavy; 0 otherwise	***0.687 (0.464)***	***0.722 (0.448)***	***0.687 (0.464)***	***0.677 (0.468)***

Table 2. *Cont.*

Variables	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
Crash characteristics				
Vehicle travel status				
1 if straight ahead; 0 otherwise	***0.751 (0.433)***	0.730 (0.444)	***0.753 (0.432)***	0.754 (0.431)
1 if right turn; 0 otherwise	***0.061 (0.239)***	0.093 (0.291)	***0.076 (0.265)***	0.067 (0.250)
1 if left turn; 0 otherwise	***0.047 (0.212)***	0.051 (0.220)	***0.047 (0.213)***	0.048 (0.213)
Crash type				
1 if head-on; 0 otherwise	0.098 (0.298)	***0.122 (0.327)***	0.116 (0.320)	0.104 (0.306)
1 if sideswipe; 0 otherwise	0.519 (0.500)	***0.563 (0.496)***	0.553 (0.497)	0.521 (0.500)
1 if rear end; 0 otherwise	0.368 (0.482)	***0.302 (0.459)***	0.313 (0.464)	0.364 (0.481)
Multi-party crashes				
1 if multi-party crashes; 0 otherwise	***0.557 (0.497)***	***0.584 (0.493)***	***0.574 (0.495)***	***0.533 (0.499)***
Crash position				
1 if motorway; 0 otherwise	***0.739 (0.440)***	0.740 (0.439)	0.727 (0.446)	0.745 (0.436)
1 if non-motorway; 0 otherwise	***0.112 (0.315)***	0.113 (0.317)	0.126 (0.331)	0.110 (0.314)
1 if mixed motorized and non-motorized lanes; 0 otherwise	***0.112 (0.315)***	0.101 (0.301)	0.106 (0.309)	0.092 (0.290)
Road characteristics				
Road type				
1 if national and provincial road; 0 otherwise	***0.486 (0.500)***	0.455 (0.498)	0.435 (0.496)	0.455 (0.498)
1 if urban road; 0 otherwise	***0.292 (0.455)***	0.297 (0.457)	0.328 (0.470)	0.309 (0.462)
1 if rural road; 0 otherwise	***0.211 (0.408)***	0.243 (0.429)	0.227 (0.419)	0.222 (0.416)
1 if high-speed road; 0 otherwise	***0.011 (0.103)***	0.005 (0.071)	0.011 (0.103)	0.013 (0.114)
Junction section type				
1 if ordinary road; 0 otherwise	***0.636 (0.481)***	0.614 (0.487)	0.616 (0.486)	***0.600 (0.490)***
1 if four-way junction; 0 otherwise	***0.295 (0.456)***	0.312 (0.463)	0.296 (0.457)	***0.320 (0.466)***
1 if three-way junction; 0 otherwise	***0.057 (0.231)***	0.058 (0.235)	0.067 (0.249)	***0.057 (0.232)***
Physical separation of roads				
1 if no segregation; 0 otherwise	0.712 (0.453)	***0.702 (0.458)***	***0.675 (0.469)***	0.689 (0.463)
1 if central segregation; 0 otherwise	0.255 (0.436)	***0.264 (0.441)***	***0.285 (0.452)***	0.275 (0.447)
Traffic control mode				
1 if no control; 0 otherwise	0.285 (0.451)	***0.259 (0.438)***	***0.266 (0.442)***	***0.268 (0.443)***
1 if signal control; 0 otherwise	0.131 (0.338)	***0.161 (0.368)***	***0.157 (0.364)***	***0.146 (0.353)***
1 if marking control; 0 otherwise	0.584 (0.493)	***0.580 (0.494)***	***0.577 (0.494)***	***0.587 (0.493)***
Road line type				
1 if non-planar linear; 0 otherwise	0.875 (0.331)	***0.853 (0.354)***	***0.850 (0.357)***	***0.850 (0.358)***
Environmental and temporal characteristics				
Road surface condition				
1 if non-dry; 0 otherwise	0.948 (0.223)	***0.927 (0.260)***	***0.895 (0.307)***	0.922 (0.268)
Lightening condition				
1 if daylight; 0 otherwise	***0.562 (0.496)***	0.584 (0.493)	0.585 (0.493)	***0.580 (0.494)***
1 if no street lights in the dark; 0 otherwise	***0.267 (0.442)***	0.222 (0.416)	0.195 (0.397)	***0.202 (0.401)***
1 if street lights in the dark; 0 otherwise	***0.126 (0.332)***	0.140 (0.347)	0.145 (0.353)	***0.127 (0.333)***
Weather				
1 if clear; 0 otherwise	***0.902 (0.298)***	0.877 (0.329)	0.819 (0.386)	***0.871 (0.335)***
1 if cloudy; 0 otherwise	***0.054 (0.227)***	0.060 (0.237)	0.093 (0.290)	***0.068 (0.251)***
1 if rainy; 0 otherwise	***0.022 (0.148)***	0.060 (0.237)	0.087 (0.282)	***0.044 (0.206)***

Table 2. *Cont.*

Variables	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
Visibility				
1 if visibility > 200 m; 0 otherwise	0.495 (0.500	0.556 (0.497)	0.515 (0.500)	0.471 (0.499)
Weekend				
1 if weekend; 0 otherwise	***0.319 (0.466)***	***0.262 (0.440)***	***0.290 (0.454)***	***0.275 (0.447)***
Crash time				
1 if peak period (7:00–8:59) (17:00–19:59); 0 otherwise	0.260 (0.439)	0.222 (0.416)	***0.236 (0.425)***	0.272 (0.445)

Note: The quarterly model variables based on the Pearson correlation test and stepwise regression are shown in bold, black, and italics.

In terms of road type, truck accidents were more likely to occur on national and provincial roads in the first quarter, on urban roads in the third quarter, and on expressways in the second quarter. From the average value of road surface factors, the number of truck collision accidents on non-dry road surfaces was higher in the first quarter than in other quarters, and the probability of accidents in the first quarter without street lights at night was high; the probability of a collision in the fourth quarter at dusk/dawn was high.

In terms of collision times, the time points with high incidences of crashes varied considerably from quarter to quarter. Mean values occurring during the flat (9:00–16:59, 20:00–6:59) peaks were higher in the second quarter than in other quarters, whereas the average value of truck collision during the morning peak (7:00–8:59) in the third quarter was the highest. In the fourth quarter, the mean value during the evening peak (17:00–19:59) was also significantly higher than that in other quarters.

4. Methodology

4.1. Random Parameters Logit Model

When modeling crash severity, traffic safety scholars proposed several modeling approaches. In previous studies, standard multinomial logit models were often used to analyze the significant influences on crash severity due to their simple structure and low error rate [21]. Mixed logit models [22], ordered probit models [18], and classification and regression tree models [23] were also used to analyze the severity of injuries in truck crashes. However, as historical data cannot record all factors that influence the severity of traffic crashes, there are always unobserved or undetected factors that impact crashes. Thus, crash data present some unobserved heterogeneity.

The subsequently developed models with heterogeneity include the Markov switching model [24], the random parameters latent class model [25], and the Bayesian heterogeneity-based approach [26]. Considering the fact that the states to be switched using the Markov switching model need to be predefined artificially, this is not conducive to the actual analysis. The method is not greatly explanatory in terms of heterogeneity at the individual level of the crash, and it is extremely difficult to construct Markov switching models with three stages or above. The Bayesian network model with heterogeneity tends to be less effective in classification when there are too many attributes or correlations. Moreover, because the prior probability needs to be assumed, the prediction effect is low, and the flexibility is low. The random parameters logit model (RPL) allows parameters to change randomly among individuals, and the heterogeneity of individuals can be characterized by the distribution of the model parameters (mean and variance). This can explain the heterogeneity of the individual level of the accidents. The model regulates heterogeneity through means and variances, providing greater flexibility in tracking unobserved heterogeneity. Moreover, its prediction effect is closer to the facts. Therefore, a random parameters logit model (RPL) considering the heterogeneity of means and variances was constructed in this study [3,7,14].

An RPL model considering the heterogeneity of means and variances was used to analyze the injury severity of truck crashes in this study. The crash injury function that determined the severity of injuries was defined as:

$$S_{ij} = \beta_i X_{ij} + \varepsilon_{ij} \tag{1}$$

where S_{ij} is the utility function for the jth crash that occurred with driver injury severity i; X_{ij} is the vector of the explaining variables (driver, vehicle, road, environment, temporal, space, etc.) that did not vary by injury severity i for the jth crash; β_i is the vector of the estimated parameters; and ε_{ij} is the error term that constitutes a standard multinomial logit model if the error obeys a generalized extreme value distribution:

$$P_{ij} = \int \frac{EXP(\beta_i X_{ij})}{\sum EXP(\beta_i X_{ij})} f(\beta|\varphi) d\beta \tag{2}$$

where P_{ij} is the probability of being injured to degree i in the jth truck crash; $f(\beta|\varphi)$ represents the probability density function of a random vector β; and φ is a vector of parameters (means and variances) of the probability density function.

To account for the heterogeneity of means and variances, β_{ij} was defined as a vector of the estimable parameters that varied across truck crashes, and it was defined as:

$$\beta_{ij} = \beta_i + \delta_{ij} M_{ij} + \sigma_{ij} e^{\omega_{ij} D_{ij}} v_{ij} \tag{3}$$

where β_i is the mean parameter estimate for all crashes with severity i; M_{ij} is an attribute vector capturing the mean heterogeneity of accident j with severity i; δ_{ij} is the corresponding vector of estimable parameters in crash j with severity i; D_{ij} is an attribute vector capturing the heterogeneity of standard deviation σ_{ij}; ω_{ij} is the corresponding parameter vector for injury severity i in crash j; and v_{ij} is a randomly distributed term capturing the unobserved heterogeneity of crash j with severity i.

M_{ij} and D_{ij} characterize the attributes of heterogeneity associated with driver, vehicle, road, environmental, and temporal characteristics. If vectors M_{ij} and D_{ij} showed significance in the random parameters logit model, then the model could characterize the unobserved heterogeneity of means and variances. If vector M_{ij} was significant in the model, the model represented only the heterogeneity of the means.

In this study, the likelihood function in the random parameters logit model was estimated using Halton sequences with fewer repetitions [27]. After studying different Halton samples, a simulated maximum likelihood method with 1000 Halton samples was used, considering the trade-off between estimation performance and computational time. Several distribution functions were attempted to evaluate the random parameters, and it was found that normal distribution provided a better statistical fit to the random parameters logit model than other density functions (e.g., uniform, lognormal, triangular). Hence, the normal distribution function was chosen. The log-likelihood function (LL) test model estimate was defined as:

$$LL = \sum_{n=1}^{N} \left(\sum_{i=1}^{I} \sigma_{ij} \left[\beta_i X_{ij} - LN \sum_{\forall I} e^{\beta_I X_{Ij}} \right] \right) \tag{4}$$

where I denotes the total number of injury severity outcomes; N denotes the sample size; and L is the likelihood function.

Marginal effects were calculated for each variable of the random parameters logit model to specify the unit contribution of individual variables. The direct marginal effects were expressed as:

$$\eta_{X_{ij}}^{P_{ij}} = \frac{dP_{ij}}{dX_{ij}} = \frac{d}{dX_{ij}} \int \frac{e^{\beta_i X_{ij}}}{\sum_{\forall I} e^{\beta_i X_{ij}}} f(\beta|\varphi) d\beta \tag{5}$$

The meaning of the parameter variables is the same as shown above.

4.2. Transferability Test

Numerous studies showed that the role of influencing factors on crash injury severity may change over time, indicating instability over time [7,14,28]. Therefore, in the modeling process, the model transferability analysis method was adopted to test the temporal stability and temporal migration of the model. In this study, the transferability test was used to analyze whether it was necessary to model crash injury severity for each of the four quarters or whether the statistical effect of using the same model in the four quarters was ideal. The temporal transferability was analyzed with two series of likelihood ratio tests.

The first series of likelihood ratio tests was used to compare the models for two separate quarters and to check whether the parameter estimates remained stable over four quarters:

$$\chi^2_{t_1} = -2\left[LL\left(\beta_{y_1y_2}\right) - LL\left(\beta_{y_1}\right)\right] \quad (6)$$

where $LL\left(\beta_{y_1y_2}\right)$ denotes the log-likelihood at the convergence of the model with parameters from y_2 using data from subgroup y_1 and $LL\left(\beta_{y_1}\right)$ denotes the log-likelihood at the convergence of the model using data from subgroup y_1. To obtain two test results for each model comparison, subgroup y_1 and subgroup y_2 were also tested inversely. The degrees of freedom were equal to the number of estimated parameters, and the χ^2 values derived from the χ^2 distributions were used to determine the confidence level. At this confidence level, the null hypothesis that the traffic crash model parameters were the same between different quarters could be accepted or rejected.

The second series of likelihood ratio tests compared the temporal stability between the mixed time model and each time model:

$$\chi^2_{t_2} = -2\left[LL\left(\beta_{\text{1st Quarter}-\text{4th Quarter}}\right) - \sum_{\text{1st Quarter}}^{\text{4th Quarter}} LL(\beta_t)\right] \quad (7)$$

where $LL\left(\beta_{1st\ \ Quarter-4th\ \ Quarter}\right)$ denotes the log-likelihood of convergence of the model based on the combined four quarters of data and $LL(\beta_t)$ denotes the log-likelihood of model convergence using only one quarter t (Q1st, Q2nd, Q3rd, and Q4th). The degree of freedom was equal to the sum of the significant parameters in each quarter minus the number of significant parameters in the entire model.

5. Results

The traditional logit model, the random parameters logit model, and the RPL model considering the heterogeneity of means and variances were employed to estimate crash injury severity on a quarterly basis. The model estimation results are shown in Tables 3–6. A separate "-" in the regression parameter column indicates that the parameter was not statistically significant at the 90% level. The higher the value of AIC was, the larger pseudo-R2 was; the higher the log-likelihood of model convergence was, the better the fit of the model was. It could be seen that the fitting performance of the RPL model considering the heterogeneity of means and variances was the best for the four quarters. In the model, a positive parameter estimation indicated an increase in the probability of crash injury severity for the explanatory variables, and a negative parameter estimation indicated a decrease in the probability. The results of the likelihood ratio tests for the different quarterly periods are shown in Table 7; they indicated that the same null hypothesis could be rejected with more than 99.99% confidence for these four quarters. According to Equation (7), the obtained χ^2 statistics could be used to test the transferability of the model estimation results for the four quarters. The value of χ^2 obtained in this test was 128.74, and the model had 24 degrees of freedom. According to the estimation results, the null hypothesis that the model could be transplanted across the four quarters was rejected at a 99.99% confidence level. The positive and negative values of the marginal effects indicated increases and decreases in the probability of occurrence. The marginal effects of the explanatory variables for each quarter are shown in Table 8.

Table 3. Model estimation of injury severity over the first quarter.

Variables	Standard Multinomial Logit Model		RPL		RPL Considering Heterogeneity of Means and Variances	
	Parameter Estimate	*p*-Value	Parameter Estimate	*p*-Value	Parameter Estimate	*p*-Value
Defined for no injury						
Constant	−2.676	0.0000	−2.562	0.0000	−3.012	0.0000
Driver age (1 if age ≥ 51; 0 otherwise)	0.879	0.0490	1.004	0.0326	1.125	0.0305
Truck type (1 if heavy; 0 otherwise)	−0.809	0.0458	−1.054	0.0124	−1.070	0.0161
Multi-party crashes (1 if multi-party crashes; 0 otherwise)	1.404	0.0035	1.559	0.0017	1.305	0.0016
Junction section type (1 if ordinary road; 0 otherwise)	−0.785	0.0442	−0.890	0.0319	−0.890	0.0256
Defined for damage injury						
Constant	−0.653	0.0332	−0.708	0.0428	−0.712	0.0430
Truck type (1 if heavy; 0 otherwise)	−0.552	0.0003	−1.346	0.0615	−0.920	0.0824
Standard deviation of heavy	-	-	3.082	0.0427	2.251	0.0527
Multi-party crashes (1 if multi-party crashes; 0 otherwise)	0.545	0.0001	2.055	0.0001	0.612	0.0001
Crash position (1 if motorway; 0 otherwise)	0.810	0.0695	2.249	0.0814	1.182	0.0829
Standard deviation of motorway	-	-	2.384	0.0428	1.605	0.0493
Crash position (1 if non-motorway; 0 otherwise)	0.932	0.0602	0.961	0.0884	0.9100	0.0887
Heterogeneity of means of random parameters						
Truck type (1 if heavy; 0 otherwise): Multi-party crashes (1 if multi-party crashes; 0 otherwise)	-	-	-	-	−1.952	0.0031
Truck type (1 if heavy; 0 otherwise): Weather (1 if cloudy; 0 otherwise)	-	-	-	-	−1.112	0.0214
Crash position (1 if motorway; 0 otherwise): Multi-party crashes (1 if multi-party crashes; 0 otherwise)	-	-	-	-	2.234	0.0343
Number of observations	938		938		938	
Log-likelihood at constant	−1030.50		−1030.50		−1030.50	
Log-likelihood at convergence	−715.15		−708.75		−702.49	
McFadden Pseudo R-Squared	0.151		0.312		0.355	
AIC	1452.3		1447.5		1442.9	

Table 4. Model estimation of injury severity over the second quarter.

Variables	Standard Multinomial Logit Model		RPL		RPL Considering Heterogeneity of Means and Variances	
	Parameter Estimate	*p*-Value	Parameter Estimate	*p*-Value	Parameter Estimate	*p*-Value
Defined for no injury						
Constant	−3.601	0.0000	−3.429	0.0000	−3.590	0.0000
Truck type (1 if heavy; 0 otherwise)	−0.876	0.0118	−1.148	0.0015	−0.852	0.0088
Multi-party crashes (1 if multi-party crashes; 0 otherwise)	1.231	0.0012	1.315	0.0028	1.221	0.0122
Traffic control mode (1 if marking control; 0 otherwise)	0.843	0.0388	0.787	0.0432	0.796	0.0189
Defined for damage injury						
Constant	0.373	0.0001	0.358	0.0001	0.331	0.0004
Crash type (1 if rear-end; 0 otherwise)	−0.383	0.0013	−0.905	0.0545	−1.045	0.0641
Standard deviation of rear-end	-	-	2.581	0.0466	2.014	0.0495
Multi-party crashes (1 if multi-party crashes; 0 otherwise)	0.237	0.0343	0.992	0.0651	0.825	0.0524
Standard deviation of multi-party crashes	-	-	2.263	0.0149	1.836	0.0210
Road surface condition (1 if non-dry; 0 otherwise)	0.375	0.0422	0.914	0.0337	0.420	0.0562
Heterogeneity of means of random parameters						
Crash type (1 if rear-end; 0 otherwise): Traffic control mode (1 if no control; 0 otherwise)	-	-	-	-	0.935	0.0401
Crash type (1 if rear-end; 0 otherwise): Traffic control mode (1 if marking control; 0 otherwise)	-	-	-	-	0.839	0.0412
Multi-party crashes (1 if multi-party crashes; 0 otherwise): Traffic control mode (1 if signal control; 0 otherwise)	-	-	-	-	−0.431	0.0385
Number of observations	1369		1369		1369	
Log-likelihood at constant	−1065.83		−1065.83		−1065.83	
Log-likelihood at convergence	−1047.69		−1045.13		−1041.18	
McFadden Pseudo R-Squared	0.197		0.305		0.337	
AIC	2145.2		2138.9		2130.4	

Table 5. Model estimation of injury severity over the third quarter.

Variables	Standard Multinomial Logit Model		RPL		RPL Considering Heterogeneity of Means and Variances	
	Parameter Estimate	*p*-Value	Parameter Estimate	*p*-Value	Parameter Estimate	*p*-Value
Defined for no injury						
Constant	−4.107	0.0000	−4.126	0.0000	−4.143	0.0000
Truck type (1 if heavy; 0 otherwise)	−0.910	0.0412	−0.655	0.0448	−1.061	0.0493
Multi-party crashes (1 if multi-party crashes; 0 otherwise)	1.623	0.0025	1.658	0.0042	1.731	0.0089
Weather (1 if cloudy; 0 otherwise)	1.146	0.0486	1.351	0.0524	1.459	0.0602
Standard deviation of cloudy	-	-	1.261	0.0251	1.075	0.0264
Defined for damage injury						
Constant	0.996	0.0000	0.982	0.0000	0.758	0.0002
Driver driving experience (1 if driving experience ≥21 years; 0 otherwise)	0.242	0.0452	0.254	0.0485	0.328	0.0490
Overload (1 if overload; 0 otherwise)	−0.660	0.0384	−0.523	0.0524	−0.692	0.0491
Truck type (1 if heavy; 0 otherwise)	−0.618	0.0000	−0.666	0.0000	−0.630	0.0000
Vehicle travel status (1 if straight ahead; 0 otherwise)	−0.414	0.0088	−0.372	0.0089	−4.138	0.0895
Vehicle driving status (1 if right turn; 0 otherwise)	−0.631	0.0123	−0.679	0.0125	−0.576	0.0220
Multi-party crashes (1 if multi-party crashes; 0 otherwise)	0.384	0.0011	0.438	0.0011	0.386	0.0021
Road line type (1 if non-planar linear; 0 otherwise)	−0.400	0.0131	−0.447	0.0132	−0.393	0.0131
Weekend (1 if weekend; 0 otherwise)	−0.339	0.0069	−0.331	0.0069	−0.303	0.0546
Standard deviation of weekend	-	-	0.879	0.0220	0.752	0.0125
Heterogeneity of means of random parameters						
Weather (1 if cloudy; 0 otherwise): Driver driving experience (1 if driving experience ≥21 years; 0 otherwise)	-	-	-	-	3.104	0.0114
Weekend (1 if weekend; 0 otherwise): Vehicle travel status (1 if straight ahead; 0 otherwise)	-	-	-	-	−0.811	0.0261
Number of observations	1306		1306		1306	
Log-likelihood at constant	−974.290		−974.290		−974.290	
Log-likelihood at convergence	−938.438		−935.792		−930.364	
McFadden Pseudo R-Squared	0.185		0.348		0.352	
AIC	1902.9		1900.5		1897.7	

Table 6. Model estimation of injury severity over the fourth quarter.

Variables	Standard Multinomial Logit Model		RPL		RPL Considering Heterogeneity of Means and Variances	
	Parameter Estimate	*p*-Value	Parameter Estimate	*p*-Value	Parameter Estimate	*p*-Value
Defined for no injury						
Constant	−3.407	0.0000	−3.401	0.0000	−3.346	0.0000
Driver driving experience (1 if driving experience <11 years; 0 otherwise)	−0.246	0.0249	−0.189	0.0284	−0.225	0.0205
Multi-party crashes (1 if multi-party crashes; 0 otherwise)	0.828	0.0080	0.826	0.0079	0.847	0.0091
Road line type (1 if non-planar linear; 0 otherwise)	−1.270	0.0126	−1.265	0.0118	−1.276	0.0195
Traffic control mode (1 if no control; 0 otherwise)	0.465	0.0291	0.451	0.0361	0.244	0.0614
Lightening condition (1 if no street lights in the dark; 0 otherwise)	1.056	0.0628	1.066	0.0685	1.092	0.0720
Defined for damage injury						
Constant	−0.773	0.0415	−0.721	0.0395	−0.698	0.0358
Multi-party crashes (1 if multi-party crashes; 0 otherwise)	0.574	0.0000	0.611	0.0000	0.622	0.0001
Weekend (1 if weekend; 0 otherwise)	−0.312	0.0097	−0.316	0.0109	−0.309	0.0173
Truck type (1 if heavy; 0 otherwise)	−0.553	0.0000	−0.610	0.0002	−0.746	0.0002
Traffic control mode (1 if marking control; 0 otherwise)	0.231	0.0294	0.215	0.0230	0.246	0.0357
Junction section type (1 if ordinary road; 0 otherwise)	1.017	0.0140	0.995	0.0131	1.278	0.0210
Standard deviation of ordinary road	-	-	0.848	0.0452	0.228	0.0731
Junction section type (1 if four-way type; 0 otherwise)	1.169	0.0069	1.125	0.0067	1.080	0.0060
Junction section type (1 if three-way type; 0 otherwise)	0.935	0.0482	0.895	0.0519	0.888	0.0406
Lightening condition (1 if no street lights in the dark; 0 otherwise)	−0.226	0.0543	-	-	-	-
Heterogeneity of means of random parameters						
Junction section type (1 if ordinary road; 0 otherwise): Traffic control mode (1 if no control; 0 otherwise)	-	-	-	-	0.652	0.0241
Junction section type (1 if ordinary road; 0 otherwise): Traffic control mode (1 if marking control; 0 otherwise)	-	-	-	-	0.713	0.0356

Table 6. *Cont.*

Variables	Standard Multinomial Logit Model		RPL		RPL Considering Heterogeneity of Means and Variances	
	Parameter Estimate	***p*-Value**	**Parameter Estimate**	***p*-Value**	**Parameter Estimate**	***p*-Value**
Junction section type (1 if ordinary road; 0 otherwise): Lighting condition (1 if no street lights in the dark; 0 otherwise)	-	-	-	-	−0.462	0.0278
Number of observations	1449		1449		1449	
Log-likelihood at constant	−1591.89		−1591.89		−1591.89	
Log-likelihood at convergence	−1103.76		−1102.46		−1094.16	
McFadden Pseudo R-Squared	0.128		0.307		0.313	
AIC	2237.5		2227.2		2213.8	

Table 7. Likelihood ratio test results for different quarterly periods.

	y_2			
y_1	**1st Quarter**	**2nd Quarter**	**3rd Quarter**	**4th Quarter**
1st quarter	-	322.82 (9) [>99.99%]	218.96 (11) [>99.99%]	351.53 (12) [>99.99%]
2nd quarter	328.59 (10) [>99.99%]	-	96.15 (11) [>99.99%]	138.88 (12) [>99.99%]
3rd quarter	244.97 (10) [>99.99%]	171.23 (9) [>99.99%]	-	141.53 (12) [>99.99%]
4th quarter	380.86 (10) [>99.99%]	166.76 (9) [>99.99%]	171.96 (11) [>99.99%]	-

Table 8. Marginal effects of explanatory variables in different quarters (RPL model considering heterogeneity of means and variances).

Variables	1st Quarter			2nd Quarter			3rd Quarter			4th Quarter		
	NI	**DI**	**FI**	**NI**	**DI**	**FI**	**NI**	**DI**	**FI**	**NI**	**DI**	**FI**
Driver characteristics												
(NI) Driver age (1 if age ≥ 51 years; 0 otherwise)	***0.0822***	−0.0021	−0.0149									
(NI) Driver driving experience (1 if driving experience <11 years; 0 otherwise)										***−0.0396***	0.0014	0.0016
(DI) Driver driving experience (1 if driving experience ≥21 years; 0 otherwise)							−0.0312	***0.0210***	−0.0112			
Vehicle characteristics												
(DI) Overload (1 if overload; 0 otherwise)							0.0071	***−0.0116***	0.0051			
(NI) Truck type (1 if heavy; 0 otherwise)	***−0.0373***	0.0065	0.0129	***−0.0802***	0.0058	0.0277	***−0.0372***	0.0042	0.0025			
(DI) Truck type (1 if heavy; 0 otherwise)	0.0162	***−0.0160***	0.0125				0.0191	**−0.192**	0.0215	0.0078	**−0.1145**	0.1067
Crash characteristics												
(DI) Vehicle travel status (1 if straight ahead; 0 otherwise)							0.0172	***−0.0139***	0.0154			
(DI) Vehicle driving status (1 if right turn; 0 otherwise							0.0227	***−0.0251***	0.0258			
(DI) Crash type (1 if rear-end; 0 otherwise)				0.1244	***−0.0945***	0.0865						
(NI) Multi-party crashes (1 if multi-party crashes; 0 otherwise)	***0.1256***	−0.0138	−0.0613	***0.0622***	−0.0164	−0.0302	***0.0792***	−0.0162	−0.0145	***0.0119***	−0.0063	−0.0056
(DI) Multi-party crashes (1 if multi-party crashes; 0 otherwise)	−0.0842	***0.0153***	−0.0244	−0.0118	***0.0130***	−0.0101	−0.0855	***0.0228***	−0.0128	−0.0037	***0.0576***	−0.0538
(DI) Crash position (1 if motorway; 0 otherwise)	−0.0393	***0.0299***	−0.0325									
(DI) Crash position (1 if non-motorway; 0 otherwise)	−0.0630	***0.0388***	−0.0221									

Table 8. *Cont.*

Variables	1st Quarter			2nd Quarter			3rd Quarter			4th Quarter		
	NI	DI	FI	NI	DI	FI	NI	DI	FI	NI	DI	FI
Road characteristics												
(NI) Junction section type (1 if ordinary road; 0 otherwise)	***−0.170***	0.0042	0.0242									
(DI) Junction section type (1 if ordinary road; 0 otherwise)										−0.0078	***0.1249***	−0.1170
(DI) Junction section type (1 if four-way type; 0 otherwise)										−0.0547	***0.0249***	−0.0495
(DI) Junction section type (1 if three-way type; 0 otherwise)										−0.0282	***0.0227***	−0.0124
(NI) Traffic control mode (1 if no control; 0 otherwise)										***0.0020***	−0.0012	−0.0008
(NI) Traffic control mode (1 if signal control; 0 otherwise)				***0.0491***	−0.0098	−0.0288						
(DI) Traffic control mode (1 if signal control; 0 otherwise)										0.0001	***−0.0023***	0.0022
(NI) Road line type (1 if non-planar linear; 0 otherwise)										***−0.0017***	0.0009	0.0008
(DI) Road line type (1 if non-planar linear; 0 otherwise)							0.0309	***−0.0291***	0.0286			
Environmental and temporal characteristics												
(DI) Road surface condition (1 if non-dry; 0 otherwise)				0.0262	***−0.0185***	0.0253						
(NI) Lightening condition (1 if daylight; 0 otherwise)										***0.0082***	−0.0046	−0.0036
(NI) Weather (1 if cloudy; 0 otherwise)							***0.0464***	−0.0037	−0.0031			
(DI) Weekend (1 if weekend; 0 otherwise)							0.0501	***−0.0482***	0.0487	0.0377	***−0.0368***	0.0354

Note: NI indicates no injury; DI indicates damage injury; FI indicates fatal injury. Bold italic values indicate injury severity outputs for defined explanatory variables.

5.1. Driver Characteristics

According to Table 8, the influencing factors showed different results across quarters. Compared with drivers under the age of 51, drivers aged 51 and over were more likely to be involved in no-injury truck crashes and less likely to have damage injuries or fatal injuries in the first quarter. The corresponding marginal effect values showed that drivers aged 51 and over were 8.22% more likely to be in no-injury crashes, 0.21% less likely to be damaged, and 1.49% less likely to be in fatal accidents in the event of a crash than younger drivers (<51 years). Similar to previous studies, older drivers performed more consistently in traffic and drove more safely than younger drivers [29,30]. Driver age was not significant in the remaining quarters.

Driver driving experience was significant in the RPL model in the third and fourth quarters. In the third quarter, drivers with more than 20 years of driving experience were 2.10% more likely to be in a damage-injury crash, and 3.12% and 1.12% less likely to be in no-injury and fatal-injury crashes, respectively, compared with other drivers with driving experience. This indicated that drivers with more than 20 years of driving experience were less likely to have no injuries and fatal injuries and more likely to have damage injuries in the third quarter, with more experienced truck drivers being indirectly associated with a lower severity of crashes [31]. Driver age was not significant in the remaining quarters. Drivers with fewer than 11 years of driving experience were more likely to be involved in damage-injury and fatal crashes in the fourth quarter, with a 3.96% reduction in the probability of being in a no-injury accident compared with drivers with ≥11 years of driving experience and a slight increase in the probability of damage and fatal crashes (0.14% and 0.16%). This suggested that drivers with less than 11 years of driving experience were less likely to have no injuries and more likely to be involved in damage and fatal crashes in the fourth quarter, which was consistent with previous research [13,32] indicating that the younger the driver was, the weaker the driving experience was, and the more likely to be involved in serious crashes they were.

5.2. Vehicle Characteristics

Overloaded trucks as well as heavy trucks were more likely to cause serious injuries and fatalities. Comparing with non-overloaded trucks, the probability of no injuries and fatality in the third quarter for overloaded trucks relatively increased, and the probability of damage injuries decreased by 1.16%. Overloading was one of the main factors contributing to truck crashes; however, inconsistently with some previous studies [33,34], the results were proved by many other studies, which showed that overloading was positively associated with the probability of serious crashes [13].

The model results revealed that heavy trucks were statistically significant in all models, with the likelihood of no-injury crashes being reduced by varying degrees in the first three quarters of traffic crashes for heavy trucks compared with the other types of trucks, with reductions of 3.73%, 8.02%, and 3.72%, respectively. Additionally, in the first, third, and fourth quarters, the likelihood of no-injury crashes decreased by 1.60%, 19.2%, and 11.45%, respectively, when the truck model was used for heavy truck. In all quarters, heavy trucks were more likely to be involved in fatal crashes than other models. It was clear that the weight of the truck had a strong relationship with fatal injuries in the event of a crash, in line with previous research [11], where the heavier the truck was, the more likely it was to cause more serious injuries and fatalities in a crash. However, some research [35] suggested that light trucks performed the worst in traffic crashes, followed by medium trucks and finally heavy trucks, which may have been due to the fact that the severity of truck driver injuries was taken as the severity of accidents in this study.

5.3. Crash Characteristics

Driving straight ahead, turning right, rear-end crash, and single-sided crashes resulted in more serious injuries and fatalities. As can be noted from the model results (Table 8), the truck driving status showed statistical significance only in the third quarter. Compared with other driving conditions, the probabilities of crashes causing injuries while going straight and turning right were lower, decreasing by 1.39% and 2.51%, respectively, and the probabilities of being involved in fatal crashes increased by 1.54% and 2.58%, respectively. This was consistent with the findings of a previous study [7], where the severity of injuries in right-turning truck accidents was generally higher.

The model results found that truck crashes were 9.45% less likely than other crash types to cause damage injuries in rear-end crashes in the second quarter, and 12.44% and 8.65% more likely to be no-injury and fatal-injury crashes, respectively, and previous studies [36,37] also showed that rear-end crashes led to serious crashes.

Otherwise, the results revealed that the likelihood of both no-injury and damage-injury crashes increased by 12.56%, 6.22%, 7.92%, and 1.19% in each quarter for multi-party crashes compared with single-party crashes, while the likelihood of damage-injury crashes increased by 1.53%, 1.30%, 2.28%, and 5.76% in each quarter, respectively. On the other hand, the probability of fatal-injury crashes decreased in all quarters. This suggested that single-party crashes involving trucks were more likely to be fatal than multi-party crashes, whereas a previous study [38] concluded that multi-vehicle crashes involving trucks resulted in more serious injuries and fatalities, which was inconsistent with this study.

Furthermore, the results also showed that in the first quarter, crash locations that occurred on motorways and non-motorways increased the likelihood of damage injuries by 2.99% and 3.88%, respectively, compared with other locations, while no-injury and fatal-injury crashes were less likely to occur.

5.4. Road Characteristics

The marginal effects of the variables across the quarters showed that the probability of a no-injury crash decreased by 17% in the first quarter for ordinary sections relative to the other junction section types, while the probability of damage and fatal crashes increased by 0.42% and 2.42%, respectively. However, in the fourth quarter, the probability of damage-injury crashes increased by 12.49%, 2.49%, and 2.27% for the intersection roadway types of ordinary, four-way, and three-way junctions, respectively, relative to the other types, while the probability of no-injury and fatal-injury crashes decreased; however, in the study by Ali Behnood [7], it was concluded that intersection-related crashes resulted in more serious injuries, including minor and serious injury accidents.

The results for the fourth quarter for no traffic control showed an increase in the likelihood of a no-injury crash of 0.2% compared with the other traffic control modes, while the probability of damage and fatality decreased. However, traffic control with marking control reduced the probability of damage by 0.23% and increased the probability of fatality in the fourth quarter. In the third quarter, junctions with marking were 4.91% more likely to be injury-free than other control modes, with a slight reduction in the likelihood of damage and fatality. This result was different from the previous conventional understanding and needs further discussion in subsequent studies.

In addition, it indicated that in the third quarter, the probability of a non-planar linear truck crash causing a damaging injury was 2.91% lower, while the probability of no-injury and fatal-injury crashes increased by 3.09% and 2.86%, respectively, compared with a planar linear road line type. However, in the fourth quarter, the likelihood of a no-injury accident decreased by 0.17%, and the likelihood of a damage injury and a fatal injury increased slightly. Overall, non-planar straight types were more likely to be involved in serious truck crashes than planar straight types. This was previously demonstrated in a number of studies [32,39–41].

5.5. Environmental and Temporal Characteristics

The model results showed that in the second quarter, non-dry road surfaces were 1.85% less likely to cause a crash with damage injuries than dry road surfaces, while the probability of a fatal crash increased by 2.53%. This suggested that non-dry road surfaces were more prone to serious crashes [42–44]. Having street lights at night was 0.82% more likely to be associated with no-injury crashes than having no street lights in the fourth quarter, while it was 0.46% and 0.36% less likely to be associated with damage and fatality crashes, respectively, and having street lights at night was effective in reducing the probability of serious crashes [42,45]. Compared with other types of weather, the probability of a no-injury crash increased by 4.64%, and the probabilities of damage injuries and fatalities decreased by 0.37% and 0.31%, respectively, with cloudy weather in the third quarter. Compared with weekdays, weekends in the third and fourth quarters were 4.82% and 3.68% less likely to be associated with damage-injury crashes and more likely to be associated with no-injury and fatal-injury crashes, respectively; many studies [19,46,47] concluded that weekends were more likely to be associated with serious crashes.

5.6. Heterogeneity of Means of Random Parameters

Table 3 shows that in the first-quarter injury severity model, the heterogeneity of the means was observed in the two indicator variables of the vehicle type of heavy truck and the crash location of motorway. For the vehicle type of heavy truck, multiple crashes and cloudy days led to a decrease in the mean value, making damage-injury crashes less likely. For the crash location of motorway, multiple crashes led to an increase in the mean value, making damage-injury crashes more likely.

Furthermore, the estimation results are provided in Table 4. They showed that in the second-quarter injury severity model, two variables generated random parameters with the heterogeneity of the means—the rear-end collision indicator variable and the multi-party accident indicator variable. For rear-end collisions, the no-control and signal-control modes increased the average value and increased the possibility of damage-injury crashes. For multi-party crashes, the no-control traffic control mode caused the mean value to decrease, making the likelihood of a damage-injury crash lower.

Moreover, as indicated in Table 5, in the third-quarter injury severity model, the weather being cloudy and the weekend indicator generated random parameters that made their means heterogeneous. For cloudy weather, drivers with more than 20 years of driving experience increased the mean value, making no-injury crashes more likely. For weekends, vehicles driving in a straight line caused their mean to decrease and the likelihood of damage-injury crashes to decrease.

Furthermore, the intersection roadway type of normal roadway produced a random parameter with the heterogeneity of the mean in the fourth-quarter injury severity model, as shown in Table 6. For this variable, the traffic control type was no control, and sign marking control increased the average value, indicating an increased likelihood of damage injury. At the same time, the lighting condition of no street lights at night decreased the mean value, indicating a decreased likelihood of injury. The possibility of damage injury decreased.

6. Discussion

From the perspective of drivers, it was found that drivers aged over 51 years old were able to reduce the probability of fatal crashes in the first quarter. This may have been due to the fact that as drivers get older, their behaviors and psychological states are more stable, and they are able to handle vehicles more steadily than younger drivers. Therefore, they are able to drive relatively safely in the first quarter under special conditions such as cold weather and snowy roads. In the third quarter, drivers with more than 20 years of driving experience can reduce the probability of fatal crashes. This is because the third quarter is the rainy season in Shandong, China. Drivers with rich driving experience have higher skills to deal with risks, which can effectively avoid vehicle collisions or effectively reduce the severity of collision accidents. Thus, when arranging truck transportation tasks, it is recommended to arrange more experienced drivers as the main drivers, and the less-skilled ones should be assigned as auxiliary drivers in the first and third season quarters. In the fourth quarter, drivers with less than 11 years of driving experience were more likely to be involved in serious crashes, because the wet and cold weather in the fourth quarter made some less-skilled drivers more prone to be involved in crashes under slippery and icy road conditions. Therefore, it is suggested that transport companies provide relevant practice and training to drivers with less driving experience in combination with quarterly characteristics and arrange experienced drivers to lead new drivers to improve their driving skills. The traffic management department should also consider designing quarterly training for truck drivers in the process of the training and testing of driving licenses. In the supervision of truck transportation, specific seasonal policies and measures should be formulated, especially for transportation in the fourth quarter.

Monitoring should focus on overloaded trucks and heavy trucks. The model results showed that overloaded trucks were more likely to be involved in fatal crashes in the third quarter, as well as heavy trucks in all quarters, because the weight of the truck was closely related to the severity of the crash. Especially in the rainy season, heavy or overloaded vehicles have long braking distances and are prone to brake failure and to steering out of control. Overloading trucks or driving heavy trucks to deliver more cargo can reduce transport costs and increase the profits of drivers and transport companies. However, it also brings a huge risk of injuries and fatalities in the event of traffic accidents. It is necessary for transportation authorities to set up checkpoints and dynamic non-stop weighing detection devices in the main sections of national and provincial highways where trucks pass [48]. Moreover, it is also crucial to formulate stricter policies and measures to strengthen the control of truck traffic during peak hours, especially in the middle of the third quarter. When inspecting passing trucks, illegal traffic behaviors such as truck overloading should be addressed the most, in order to make sure that all the trucks are monitored and strictly inspected. Once vehicles adopting illegal behaviors are identified, they should be punished strictly, in accordance with the provisions. The owners and managers of transportation companies should deepen their understanding of the seriousness of overloading and avoid the overloading of trucks from the source. Moreover, some special training and education should be provided for heavy truck drivers to improve their driving skills. Truck drivers should also improve their professional quality, so that even if an accident occurs, the severity of the collision can be reduced as much as possible.

With regard to the types of crashes, attention should be focused on the right-hand turning of trucks and rear-end crashes. The probability of a crash with damage injuries decreased and the probability of a fatality increased in the third quarter when trucks drove straight or turned right. As shown in Table 2, the number of straight-driving and right-turning crashes in the third quarter was the largest, reflecting that the third quarter was a significant factor. Trucks are more likely to suffer serious injuries and fatalities during right turns due to problems such as blind spots in their field of vision. In order to solve the vision problem, blind area warning devices could be installed in the truck rear-view mirror and other suitable positions. When detecting a potential danger in this area, the devices should offer a sound or photoelectric signal to drivers [49]. Millimeter wave radar could also be installed to provide an audible and visual alarm based on radar detection [50]. The traffic police department could set up a sign to stop trucks when turning right at an intersection to make truck drivers pay more attention to traffic approaching from the sides [51]. The probability of fatal accidents in the second quarter was increased due to rear-end collisions. This indicated that rear-end collisions caused more serious damage and fatalities. This is a result of the fact that roads are in good conditions in the second quarter, and drivers tend to frequently overspeed and overtake. It may also be that drivers are prone to drowsiness and fatigue due to the temperature and other related reasons in the second quarter. On the one hand, the drivers of trucks are prone to rear-end collisions with other vehicles due to fatigue driving. On the other hand, other vehicles are also prone to rear-end crash with large trucks due to fatigue driving. This requires the driver to get adequate sleep and proper rest intervals when driving and to keep a safe by maintaining a distance from the vehicle in front, especially when there is a large truck in front. Moreover, they should not follow large trucks for a long time. Rear collision prevention devices could also be installed to ensure proper speed and safe distance [52]. In the first quarter, the probability of truck injuries on motorways and non-motorways increased. This may have been because the first quarter includes Spring Festival transportation, and the traffic volume on the roads increases extremely, resulting in more road crashes. In addition, the illegal parking of trucks occupying non-motorized lanes is also likely to cause injury accidents, such as electric bicycle collisions with stationary trucks. This requires the traffic management department to strengthen the supervision of trucks in key road sections and time periods, scientifically and rationally plan truck driving paths and parking locations, and strengthen the education and training of drivers.

In terms of road characteristics, intersections and roads that were not flat and straight were more likely to cause serious injuries and fatalities. The probability of traffic accidents causing injuries increased in road sections of three-way crossing and four-way crossing intersections in the first quarter and the fourth quarter. The reason may have been that these two quarters are exactly in winter and spring. The cold, rainy, and snowy weather increases, and roads easily freeze, leading to truck collision accidents that are prone to cause injuries. In order to avoid crashes, the traffic management department should strengthen supervision and law enforcement and arrange timely de-icing and snow removal in icy and snowy sections, and the driver should be reminded to slow down under slippery road conditions through intelligent means such as electronic displays and Internet of Things (IoT) maps [8]. The driver should also decelerate and keep a safe distance. Compared with signal-control junctions, no-control and marking-control junctions were less likely to cause damage-injury crashes. This may have been due to truck drivers paying special attention to passing vehicles at unsignalized intersections and driving more carefully, thus reducing the probability of crashes. In the third and fourth quarters, non-straight roads were more likely to lead to increased crash severity. The reason is that during these two quarters, the rainy and snowy weather increases, and the roads are wet and icy; thus, vehicles easily slip when turning. Moreover, non-flat and non-straight roads limit the driver’s vision and lack corresponding deceleration prevention measures, which easily makes vehicles lose control and cause serious crashes. This requires the road designer to lay a thin layer of pavement for non-flat and non-straight road sections; anti-sideslip wheel guards should be provided to prevent vehicles from sideslipping on roads in rainy and snowy weather; and linear guidance signs and delineators should be set in sections with bad terrain conditions and frequent accidents [53].

Non-dry roads, no street lighting at night, and crash times on weekends all contributed to more serious crashes. The reason for more serious crashes on non-dry roads in the second quarter may have been that if trucks run too fast on non-dry roads, tire traction is reduced, causing the wheels to slip. Drivers should drive carefully on non-dry roads and limit the speed, especially when the road is in good conditions in the second quarter. In the fourth quarter, having street lights at night could reduce the probability of serious crashes more effectively than the absence of street lights. This may have been due to the short day and long night in the fourth quarter; moreover, the presence of street lighting at night had a significant impact on the probability of traffic crashes. The relevant management department should provide the right street lighting facilities to increase visibility and reduce night-time crashes [54]. In addition, as it gets dark earlier in the fourth quarter, the lighting facilities should be turned on earlier in accordance with light intensity. In the third and fourth quarters, serious traffic accidents were more likely to occur on weekends than on weekdays, because drivers were less likely to travel on weekends than on weekdays. In addition, the changes in traffic volume and road conditions also increased the probability of accidents on the weekend. Based on this phenomenon, transport companies should focus on providing professional training and warning education for drivers on weekends, especially in the third and fourth quarters, and traffic authorities should strengthen the supervision and management of weekend traffic [7].

Based on random parameters heterogeneity, in the first quarter, drivers should focus on being aware of multi-party crashes when driving normally on the motorway, keep the appropriate speed, and maintain a safe distance among vehicles. In the second quarter, drivers should improve their predictive skills to avoid rear-end crashes when passing through no-control and marking-control intersections. In the third quarter, drivers with more than 20 years of driving experience were more likely to be involved in crashes on cloudy days due to the increase in age and the decrease in vision. Therefore, it is recommended that younger truck drivers should be assigned as the main drivers and that the older ones should be assigned as the auxiliary drivers when driving on cloudy days. In the fourth quarter, when the traffic control mode is no control or marking control, while entering an ordinary road section from an intersection, the driving could be too fast with no vehicles or a few vehicles in front, which increases the probability of injury crashes. This requires drivers to slow down and drive cautiously during the transition period from crossings to ordinary road sections.

7. Conclusions

Truck crash data for 10 years (2012–2021) were collected to examine the impact of the four quarters of a year on truck crashes. Using persons most seriously injured in a crash as the subjects of the study, the three injury severity levels of no injury, damage injury, and fatal injury were considered, and various factors affecting the severity of truck crash injuries were analyzed in terms of driver, vehicle, crash type, road, and environmental and temporal characteristics.

Through the comparison of the three estimation models, it was found that the random parameters logit model considering the heterogeneity of the means and variances had a higher goodness-of-fit. The likelihood ratio test showed that the effects of the factors determining injury severity varied significantly across quarters. However, there were also explanatory variables that had a stabilizing effect in terms of quarterly effects on the severity of injuries caused by trucks. For example, heavy trucks increased the likelihood of fatal crashes in all quarters, and multiple crashes increased the likelihood of no-injury and damage-injury crashes and decreased the probability of fatal crashes in all quarters.

This study revealed the quarterly stability of the factors influencing the severity of truck crash injuries. Changes in the variables can be used by policymakers to better formulate transport policies; for example, as heavy trucks are more likely to cause fatal crashes than other types of trucks, special training should be given to drivers of heavy trucks to increase their safety awareness. Overloaded trucks should be strictly investigated and punished, and transport times and routes should be reasonably adjusted according to the characteristics of each season.

The influencing factors and statistical methods considered in this research study can be further optimized and enriched. Only temporal stability was considered in this study; future research should consider the influence of spatial stability and discuss the spatial and temporal changes in the region. In the future, more advanced theoretical methods need to be established to enhance the transferability of the crash model. Other influencing factors can also be considered, such as traffic flow on the road, the travel speed of the truck, driver behavior, and other indicator variables.

Author Contributions: Study conception and design, F.W., P.L. and Y.G.; data collection, D.D. and Q.L.; data analysis and interpretation of results, Z.W. and Q.L.; draft manuscript preparation, F.W., D.D. and Y.G.; manuscript revision, Y.G., F.W. and Z.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research study was jointly supported by (1) National Natural Science Foundation of China (grants Nos. 71901134 and 71871057); (2) National Science Foundation for Distinguished Young Scholars (grant No. 51925801).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author. The data are not publicly available due to security and privacy issues.

Acknowledgments: The authors are thankful for the support of the Shandong Department of Transportation (SDOT), the Zibo Department of Transportation (ZDOT), and the Center for Accident Research in Zibo (CARZ).

Conflicts of Interest: 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. 2021. Available online: https://xxgk.mot.gov.cn/2020/jigou/zhghs/202205/t20220524_3656659.html (accessed on 25 May 2022).
2. Institute of Highway Science, Ministry of Transport. China Road Freight Industry Operation Analysis Report Based on Big Data. 2020. Available online: https://www.163.com/dy/article/GLSGJ67N05388W2A.html (accessed on 25 May 2022).
3. Behnood, A.; Mannering, F. Time-of-day variations and temporal instability of factors affecting injury severities in large-truck crashes. Anal. *Methods Accid. Res.* **2019**, *23*, 100102. [CrossRef]
4. 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. Available online: http://www.stats.gov.cn/tjsj/zxfb/202002/t20200228_1728913.html (accessed on 25 May 2022).
5. 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, 2022. Available online: http://www.stats.gov.cn/tjsj/zxfb/202202/t20220227_1827960.html (accessed on 25 May 2022).
6. United States Department of Labor. USA-USDL. 2017. Available online: https://www.osha.Gov/SLTC/trucking_industry/safetyinfo.html (accessed on 25 May 2022).
7. Behnood, A.; Saleem, N.; Al-Bdairi, S. Determinant of injury severities in large truck crashes: A weekly instability analysis. *Saf. Sci.* **2020**, *131*, 104911. [CrossRef]
8. Ahmeda, M.M.; Franke, R.; Ksaibati, K.; Shinstine, D.S. Effects of truck traffic on crash injury severity on rural highways in Wyoming using Bayesian binary logit models. *Accid. Anal. Prev.* **2018**, *117*, 106–113. [CrossRef]
9. Uddin, M.; Huynh, N. Injury severity analysis of truck-involved crashes under different weather conditions. *Accid. Anal. Prev.* **2020**, *141*, 105529. [CrossRef] [PubMed]
10. Chen, F.; Chen, S. Injury severities of truck drivers in single- and multi-vehicle accidents on rural highways. *Accid. Anal. Prev.* **2011**, *43*, 1677–1688. [CrossRef] [PubMed]
11. Zheng, Z.; Lu, P.; Lantz, B. Commercial truck crash injury severity analysis using gradient boosting data mining model. *J. Saf. Res.* **2018**, *65*, 115–124. [CrossRef] [PubMed]
12. Behnood, A.; Mannering, F. Determinants of bicyclist injury severities in bicycle-vehicle crashes: A random parameters approach with heterogeneity in means and variances. *Anal. Methods Accid. Res.* **2017**, *16*, 35–47. [CrossRef]
13. Wang, Y.; Prato, C.G. Determinants of injury severity for truck crashes on mountain expressways in China: A case-study with a partial proportional odds model. *Saf. Sci.* **2019**, *117*, 100–107. [CrossRef]

14. Wang, C.; Chena, F.; Zhang, Y.; Cheng, J. Spatiotemporal instability analysis of injury severities in truck-involved and non-truck-involved crashes. *Anal. Methods Accid. Res.* **2022**, *34*, 100214. [CrossRef]
15. Khorashadi, A.; Niemeier, D.; Shankar, V.; Mannering, F. Differences in rural and urban driver-injury severities in accidents involving large-trucks: An exploratory analysis. *Accid. Anal. Prev.* **2005**, *37*, 910–921. [CrossRef]
16. Apronti, D.T.; Saha, P.; Moomen, M.; Ksaibati, K. Truck safety evaluation on Wyoming mountain passes. *Accid. Anal. Prev.* **2019**, *122*, 342–349. [CrossRef]
17. Hao, W.; Kamga, C.; Yang, X.; Ma, J.; Thorson, E.; Zhong, M.; Wu, C. Driver injury severity study for truck involved accidents at highway-rail grade crossings in the United States. *Transp. Res. Part F Traffic Psychol. Behav.* **2016**, *43*, 379–386. [CrossRef]
18. Zhu, X.; Srinivasan, S. Modeling occupant-level injury severity: An application to large-truck crashes. *Accid. Anal. Prev.* **2011**, *43*, 1427–1437. [CrossRef] [PubMed]
19. Adanu, E.K.; Hainen, A.; Jones, S. Latent class analysis of factors that influence weekday and weekend single-vehicle crash severities. *Accid. Anal. Prev.* **2018**, *113*, 187–192. [CrossRef] [PubMed]
20. Yu, H.; Li, Z.; Zhang, G.; Liu, P. A latent class approach for driver injury severity analysis in highway single vehicle crash considering unobserved heterogeneity and temporal influence. *Anal. Methods Accid. Res.* **2019**, *24*, 100110. [CrossRef]
21. Wu, Q.; Zhang, G.; Ci, Y.; Wu, L.; Tarefder, R.A.; Alcántara, A.D. Exploratory multinomial logit model–based driver injury severity analyses for teenage and adult drivers in intersection-related crashes. *Traffic Inj. Prev.* **2016**, *17*, 413–422. [CrossRef]
22. Islam, M.B.; Hernandez, S. Modeling injury outcomes of crashes involving heavy vehicles on Texas highways. *Transport. Res. Rec.* **2013**, *2388*, 28–36. [CrossRef]
23. Behnood, A.; Mannering, F.L. An empirical assessment of the effects of economic recessions on pedestrian-injury crashes using mixed and latent-class models. *Anal. Methods Accid. Res.* **2016**, *12*, 1–17. [CrossRef]
24. Malyshkina, N.V.; Mannering, F.L. Markov switching multinomial logit model: An application to accident-injury severities. *Accid. Anal. Prev.* **2009**, *41*, 829–838. [CrossRef]
25. Xiong, Y.; Mannering, F.L. The heterogeneous effects of guardian supervision on adolescent driver-injury severities: A finite-mixture random-parameters approach. *Transport. Res. B Meth.* **2013**, *49*, 39–54. [CrossRef]
26. Boggs, A.M.; Wali, B.; Khattak, A.J. Exploratory analysis of automated vehicle crashes in California: A text analytics & hierarchical Bayesian heterogeneity-based approach. *Accid. Anal. Prev.* **2020**, *135*, 105354. [CrossRef] [PubMed]
27. Bhat, C.R. Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. *Transport. Res. B Meth.* **2003**, *37*, 837–855. [CrossRef]
28. Islam, M.; Alnawmasi, N.; Mannering, F. Unobserved heterogeneity and temporal instability in the analysis of work-zone crash-injury severities. *Anal. Methods Accid. Res.* **2020**, *28*, 100130. [CrossRef]
29. Hamido, S.; Hamamoto, R.; Gu, X.Z.; Itoh, K. Factors influencing occupational truck driver safety in ageing society. *Accid. Anal. Prev.* **2021**, *150*, 105922. [CrossRef] [PubMed]
30. Newnam, S.; Koppel, S.; Molnar, L.J.; Zakrajsek, J.S.; Eby, D.W.; Blower, D. Older truck drivers: How can we keep them in the workforce for as long as safely possible? *Saf. Sci.* **2020**, *121*, 589–593. [CrossRef]
31. Mehdizadeh, M.; Shariat-Mohaymany, A.; Nordfjaern, T. Accident involvement among Iranian lorry drivers: Direct and indirect effects of background variables and aberrant driving behaviour. *Transp. Res. Part F Traffic Psychol. Behav.* **2018**, *58*, 39–55. [CrossRef]
32. Haq, M.T.; Zlatkovic, M.; Ksaibati, K. Investigating occupant injury severity of truck-involved crashes based on vehicle types on a mountainous freeway: A hierarchical Bayesian random intercept approach. *Accid. Anal. Prev.* **2020**, *144*, 105654. [CrossRef]
33. Lemp, J.; Kockelman, K.; Unnikrishnan, A. Analysis of large truck crash severity using heteroskedastic ordered probit models. *Accid. Anal. Prev.* **2011**, *43*, 370–380. [CrossRef]
34. Chu, H. An investigation of the risk factors causing severe injuries in crashes involving gravel trucks. *Traffic Inj. Prev.* **2012**, *13*, 355–363. [CrossRef]
35. Castillo-Manzanoa, J.I.; Castro-Nuñoa, M.; Castro-Nuñoa, M.; Fageda, X. Exploring the relationship between truck load capacity and traffic accidents in the European Union. *Transp. Res. Part E Log.* **2016**, *88*, 94–109. [CrossRef]
36. Chang, L.; Chien, J.T. Analysis of driver injury severity in truck-involved accidents using a non-parametric classification tree model. *Saf. Sci.* **2013**, *51*, 17–22. [CrossRef]
37. Uddin, M.; Huynh, N. Factors influencing injury severity of crashes involving HAZMAT trucks. *Int. J. Transp. Sci. Technol.* **2017**, *7*, 1–9. [CrossRef]
38. Abdeen, M.M.; Ghasemzadeh, A. The impacts of heavy rain on speed and headway Behaviors: An investigation using the SHRP2 naturalistic driving study data. *Transp. Res. Part C Emerg Technol.* **2018**, *21*, S3–S12. [CrossRef]
39. Islama, M.; Hosseini, P.; Jalayer, M. An analysis of single-vehicle truck crashes on rural curved segments accounting for unobserved heterogeneity. *J. Saf. Res.* **2022**, *80*, 148–159. [CrossRef] [PubMed]
40. Haq, M.T.; Zlatkovic, M.; Ksaibati, K. Assessment of commercial truck driver injury severity based on truck configuration along a mountainous roadway using hierarchical Bayesian random intercept approach. *Accid. Anal. Prev.* **2021**, *162*, 106392. [CrossRef]
41. Yuan, Y.; Yang, M.; Guo, Y.; Rasouli, S.; Gan, Z.; Ren, Y. Risk factors associated with truck-involved fatal crash severity: Analyzing their impact for different groups of truck drivers. *J. Saf. Res.* **2021**, *76*, 154–165. [CrossRef]
42. Chen, M.; Chen, P.; Gao, X.; Yang, C. Examining injury severity in truck-involved collisions using a cumulative link mixed model. *J. Transp. Health.* **2020**, *19*, 100942. [CrossRef]

43. Rahimia, E.; Shamshiripour, A.; Samimi, A.; Mohammadian, A. Investigating the injury severity of single-vehicle truck crashes in a developing country. *Accid. Anal. Prev.* **2020**, *137*, 105444. [CrossRef]
44. Zou, W.; Wang, X.; Zhang, D. Truck crash severity in New York city: An investigation of the spatial and the time of day effects. *Accid. Anal. Prev.* **2017**, *99*, 249–261. [CrossRef]
45. Moomen, M.; Rezapour, M.; Ksaibati, K. An investigation of influential factors of downgrade truck crashes: A logistic regression approach. *Orig. Res. Pap.* **2019**, *6*, 185–195. [CrossRef]
46. Cerwick, D.M.; Gkritza, K.; Shaheed, M.S.; Hans, Z.A. Comparison of the mixed logit and latent class methods for crash severity analysis. *Anal. Methods Accid. Res.* **2014**, *3–4*, 11–27. [CrossRef]
47. Quddus, M.A.; Wang, C.; Ison, S.G. Road traffic congestion and crash severity: Econometric analysis using ordered response models. *J. Transp. Eng.* **2010**, *136*, 424–435. [CrossRef]
48. Alkhoori, F.A.; Maghelal, P.K. Regulating the overloading of heavy commercial Vehicles: Assessment of land transport operators in Abu Dhabi. *Transp. Res. Part A Pol.* **2021**, *154*, 287–299. [CrossRef]
49. Wang, Q.; Wang, N.; Huang, Y.; Luan, H. Failure mechanism of right-turning mirrors of semi-trailer trains. *J. Changan. Univ: Nat Sci Ed.* **2020**, *40*, 117–126. [CrossRef]
50. Huang, X.; Xiang, Y.; Chen, G.; Li, W. Design of right-turn blind zone monitoring device for large vehicles. *Combust. Eng. Access.* **2021**, *19*, 198–199. [CrossRef]
51. Gao, Y.; Zhou, Q.; Chai, C.; Wong, Y.D. Safety impact of right-turn waiting area at signalised junctions conditioned on driver's decision-making based on fuzzy cellular automata. *Accid. Anal. Prev.* **2019**, *123*, 341–349. [CrossRef]
52. Harb, R.; Radwan, E.; Yan, X.; Abdel-Aty, M. Light truck vehicles (LTVs) contribution to rear-end collisions. *Accid. Anal. Prev.* **2007**, *39*, 1026–1036. [CrossRef]
53. Sun, Q. The temporal instability of factors affecting crash injury severity in truck-car crashes. Master's Thesis, Chang'an University, Xi'an, China, 2021.
54. Cai, Z.; Wei, F.; Wang, Z.; Guo, Y.; Chen, L.; Li, X. Modeling of low visibility-related rural single-vehicle crashes considering unobserved heterogeneity and spatial correlation. *Sustainability* **2021**, *13*, 7438. [CrossRef]