stats

MDPI

Article

An Analysis of the Impact of Injury Severity on Incident Clearance Time on Urban Interstates Using a Bivariate Random-Parameter Probit Model

M. Ashifur Rahman [1,2,*], Milhan Moomen [1,2], Waseem Akhtar Khan [1] and Julius Codjoe [1,2]

[1] Department of Civil Engineering, University of Louisiana at Lafayette, Lafayette, LA 70504, USA
[2] Louisiana Transportation Research Center, 4101 Gourrier Ave, Baton Rouge, LA 70808, USA
* Correspondence: ashifur@louisiana.edu

Abstract: Incident clearance time (ICT) is impacted by several factors, including crash injury severity. The strategy of most transportation agencies is to allocate more resources and respond promptly when injuries are reported. Such a strategy should result in faster clearance of incidents, given the resources used. However, injury crashes by nature require extra time to attend to and move crash victims while restoring the highway to its capacity. This usually leads to longer incident clearance duration, despite the higher amount of resources used. This finding has been confirmed by previous studies. The implication is that the relationship between ICT and injury severity is complex as well as correlated with the possible presence of unobserved heterogeneity. This study investigated the impact of injury severity on ICT on Louisiana's urban interstates by adopting a random-parameter bivariate modeling framework that accounts for potential correlation between injury severity and ICT, while also investigating unobserved heterogeneity in the data. The results suggest that there is a correlation between injury severity and ICT. Importantly, it was found that injury severity does not impact ICT in only one way, as suggested by most previous studies. Also, some shared factors were found to impact both injury severity and ICT. These are young drivers, truck and bus crashes, and crashes that occur during daylight. The findings from this study can contribute to an improvement in safety on Louisiana's interstates while furthering the state's mobility goals.

Keywords: incident clearance time; injury severity; interstate; bivariate probit; random parameters

check for updates

Citation: Rahman, M.A.; Moomen, M.; Khan, W.A.; Codjoe, J. An Analysis of the Impact of Injury Severity on Incident Clearance Time on Urban Interstates Using a Bivariate Random-Parameter Probit Model. *Stats* **2024**, *7*, 863–874. https://doi.org/10.3390/stats7030052

Academic Editor: Wei Zhu

Received: 10 July 2024
Revised: 29 July 2024
Accepted: 30 July 2024
Published: 9 August 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Traffic incidents, such as vehicular crashes, breakdowns, construction-related closures, adverse weather conditions, or distinctive non-emergency circumstances like sporting events, are non-recurrent events that can considerably reduce roadway capacity or lead to an abnormal increase in traffic demand [1,2]. The substantial attention given to these incidents in both academic and industry contexts arises from their unpredictable nature and the extensive impact they have on traffic flow and safety.

Vehicular crashes are one of the most frequent events requiring multi-agency incident response on roadways. In particular, vehicular crashes on interstate highways, due to their high-speed and heavy traffic conditions, not only cause fatalities and severe injuries but also negatively affect mobility and economic productivity [3]. Crashes on interstates also present notable challenges for traffic incident response management due to the expansive geographic spread [4]. These incidents further amplify in implication due to secondary crashes and substantial congestion [2,5].

An estimate by the National Highway Traffic Safety Administration (NHTSA) suggests that crashes on interstates, depending on the severity of the incident; can result in costs per hour of delay that can be up to 72 times higher than on local streets in urban areas and up to 652 times higher than in rural areas [6]. At the state level, the Federal Highway Administration (FHWA) emphasizes tracking and setting up goals for travel time reliability

measures such as a travel time index (a measure of average congestion) and a planning time index (95th percentile travel time to the free flow travel time) to ensure that non-recurrent congestion is under control [7,8]. In this field, traffic incident management (TIM) by the Departments of Transportation (DOTs) makes it a huge priority to have a rapid and effective response to traffic incidents for restoring normal traffic conditions.

The relation between incident clearance time (ICT) and crash injury severity has been established in numerous studies [9–12]. Clearance times for crash-related incidents are generally longer in comparison to other incident types. By nature, crashes involving injuries and fatalities require a multi-agency response effort to attend to such incidents. This may lead to a longer clearance time due to the extra work required to coordinate these responses as well as the time needed to attend to victims. Also, incidents that involve crashes may also require police investigations and documentation, which adds to the incident duration. However, the strategy of most agencies with respect to incident management is to respond more quickly when injuries are reported. This means that more resources (for example, more manpower and equipment) are allocated to severe crashes to quickly clear the incident of the roadway and restore the highway to its capacity. The higher resources allocated may consequently result in a reduced incident duration in comparison to other incidents which do not have the advantage of such urgency and promptness. However, the majority of studies have reported an increase in ICT with higher crash severities [9,13]. The implication is that the relationship between injury severity and incident duration is not straightforward. Additionally, several unobserved factors may actually be impacting ICT for crashes such as the training of responders, the degree of coordination between agencies, and the accessibility of the crash location.

The traditional approach adopted by most researchers in analyzing the impact of injury severity on incident duration has been to include severity as an independent variable in the analysis. However, these studies failed to take into proper account the potential correlations of inter-related variables that influence both injury severity and ICT. To this end, this study examines factors that influence ICT and crash injury severity while simultaneously accounting for unobserved heterogeneity that may affect ICT. A bivariate probit model that accounts for the correlation between injury severity and ICT was used for this study. The results of this study can further the understanding of how incidents affect ICT.

2. Literature Review

To date, a multitude of studies have been conducted to analyze factors that affect incident duration. Previous studies have found that the severity and the number of people involved influence incident duration [10,11,14,15]. Other factors that have been found to impact incident duration include the number of lanes impacted by the incident [16,17], weather conditions [11,18], and time of day [9,14,16].

The vast majority of researchers engaged in incident duration modeling have relied on hazard-based duration analysis. Hazard-based duration models establish the relationship between the duration of an incident and the probability that the duration of the incident will end in the next short time interval [11]. Covariates are sometimes included in hazard models, which operate under the assumption that these covariates act multiplicatively on a baseline hazard function [19]. These models are referred to as accelerated failure time models (AFTs). Different parametric distributions including Weibull, log-normal, and log-logistic distributions can be specified for the AFT model.

Golob et al. analyzed the severity and incident duration of truck-involved incidents using an AFT model with a log-normal distribution with incident data from Los Angeles [15]. It was found that non-injury crashes with rear-end, and sideswipe collsions had the shortest incident durations. Single-truck vehicle crashes were found to be more severe than two-vehicle crashes in terms of injuries and fatalities. In particular, hit object crashes were found to result in a longer incident duration. However, their study failed to explicitly link incident duration to injury severity. Another study predicted the severity and duration of crash-related incidents [20]. The study used an ordered probit model and a hazard-based

duration model with different distributions to predict crash severity and the duration of crash-related incidents, respectively. A support vector machine model was also used to predict crash severity and was eventually compared with the ordered probit model. The results of the study showed that fatalities and injuries increased incident duration. However, the study failed to investigate the correlation between crash severity and incident duration. The authors indicated in their analysis that it is necessary to combine predictions of crash severity and duration in one model system.

Other studies have considered the impact of crash injury severity on incident duration by considering severity as an independent variable [10,16]. It is then regressed against incident duration, the response variable, along with several other independent variables. Though this approach establishes a relationship between incident duration and injury severity, it fails to account for correlation between the two. Also, such a framework does not allow for a simultaneous analysis of the inter-relationships between variables that affect both incident duration and crash injury severity simultaneously.

From the foregoing, it is clear that several studies have analyzed the impact of injury severity on incident duration. However, the authors did not find a study that has investigated the impact of injury severity on incident duration by employing a simultaneous modeling approach. This study seeks to fill this knowledge gap by employing a bivariate probit model to investigate the inter-relationships of factors simultaneously impacting incident duration and injury severity. Specifically, the contributions of this study are to (i) investigate factors that contribute to ICT and injury severity on Louisiana's interstates, and (ii) to understand the inter-relationships between incident duration and injury severity.

3. Methodology

The bivariate random-parameter logit model is a statistical model used in choice modeling and econometrics to analyze discrete choice data where individuals make decisions among multiple alternatives. It extends the traditional random-parameter logit model by allowing for correlation between the random parameters across two or more choice dimensions.

This study hypothesizes that injury severity impacts the duration of incident clearance. To find the effect of injury severity on ICT, it is important to predict the probability of a long ICT, depending on whether an injury crash has occurred or not. This is achieved by treating the injury crash as an instrument variable. That is, the injury severity variable is first estimated from a model and the estimated value is then used as an explanatory variable instead of the observed value. This would mean that the injury severity variable while serving as a dependent variable in the severity model would also serve as an independent variable in the incident clearance model. An easy solution to this would require two logistic regression models to establish the association between injury crashes and ICT. However, this raises an issue with heterogeneity, as a dependent variable in one model cannot be used as an explanatory variable in another model [21,22].

To overcome this limitation, several traffic safety studies have utilized bivariate probit models to jointly model inter-related response variables [23–26]. The use of the bivariate probit model is advantageous as it is able to account for the potential correlation of "unobserved" effects between inter-related responses, such as the occurrence of injury crashes and the duration of incident clearance.

The bivariate probit model is specified as follows [19,27]:

$$\begin{aligned} Z_{i,1} &= \beta_{i,1} X_{i,1} + \varepsilon_{i,1}, \quad y_{i,1} = 1 \; if \; Z_{i,1} > 0, \; and \; y_{i,1} = 0 \; otherwise \\ Z_{i,1} &= \beta_{i,2} X_{i,2} + \varepsilon_{i,2}, \quad y_{i,2} = 1 \; if \; Z_{i,2} > 0, \; and \; y_{i,2} = 0 \; otherwise \end{aligned} \tag{1}$$

and the cross-equation correlated error term is defined as follows:

$$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right] \tag{2}$$

where $Z_{i,1}$ is the latent response variable indicating whether an injury crash has occurred, $y_{i,1}$ is the observed choice (1 = injury crash, 0 = no injury crash), $Z_{i,2}$ is the latent variable indicating whether the ICT is long, and $y_{i,2}$ is the observed choice for ICT (1 = long clearance time, 0 = short clearance time). Also, X is a vector of explanatory variables related to the observed choices, β is a vector of estimable parameters, and ε is a random error term (assumed to be normally distributed with zero mean and a variance of one).

The bivariate probit model setup allows the two choices to be sequentially inter-related by predicting the possible outcome of the first and second choice models based on the possible outcome of the first choice model. In other words, the dependent variable in the first model Z_1 is defined as one of the independent variables in the second choice model Z_2. From the model specification, if the two choices (Z_1 and Z_2) are inter-related, this would mean that the two error terms (ε_1 and ε_2) are correlated. Just as in any other probit model, estimated positive coefficients are associated with a higher likelihood of $y_1 = 1$ and $y_2 = 1$, as the values of the independent variables increase and vice versa.

Research has shown that the effects of explanatory variables may vary across observations due to unobserved heterogeneity [28–31]. Heterogeneity refers to latent factors that may vary systematically across observations. A random-parameter approach is applied to account for heterogeneity across the observations. The random parameter is defined as follows:

$$\beta_j = \beta + \varepsilon_j \tag{3}$$

where β is a vector of estimable parameters, and ε_j is a randomly distributed error term with a mean of zero and a variance of σ^2. To evaluate the statistical superiority of the random-parameter model specification, a likelihood ratio test was conducted. The likelihood ratio test [19] is specified by Equation (4).

$$\chi^2 = -2\left[LL(\beta_i) - LL(\beta_j)\right] \tag{4}$$

where $LL(\beta_i)$ is the log-likelihood at convergence of the fixed-parameter bivariate model, and $LL(\beta_j)$ is the log-likelihood at convergence of the random-parameter bivariate probit model. The test statistic is χ^2 distributed with degrees of freedom equal to the difference in the number of model parameters between the two model specifications.

4. Data

Data Preparation

The Louisiana highway crash databases are comprehensive compilations of crash-related information, compiled from multiple tables detailing roadway conditions, driver characteristics, and specific crash details, encompassing incidents involving all road users as reported by law enforcement officers. Crash information with limited attributes can be accessed from the user-restricted online repository, "Crash1" [32]. This study used specially accessed versions of the data, which included detailed incident response information, thereby enabling the extraction of precise incident duration times. The data encompassing interstate crashes spanning three years (2017–2019) were compiled, focusing on crash variables encompassing the roadway, driver, and crash environment with the potential to influence both crash injury severity and incident durations. In the context of this study, the dataset was systematically restructured into a crash-centric format, where each record distinctly represents an individual crash incident. Table 1 provides an overview of the different traffic incident-related variables considered for the analysis, showcasing statistics such as their mean values and standard deviations. Injury severity data were categorized on a scale from KABCO to KABC (K: Fatal Injury, A: Incapacitating Injury (disabling), B: Non-Incapacitating Evident Injury, C: Possible Injury (not evident), and O (No Injury). A binary variable was created for the injury severity category, with KABC categorized as injury (coded 1) and O categorized as no injury (coded 0). For this study, ICT is defined as the length of time between notification of an incident and the opening of all roadway lanes to traffic. ICT was dichotomized between a duration of more than thirty minutes

(long clearance time) and less than thirty minutes (short clearance time), as identified in standard traffic management analysis [33].

Table 1. Descriptive statistics of some variables used in model.

Variable Category	Type	Description	Mean	Standard Deviation
Response				
ICT	Binary	Long clearance (ICT > 30 min)	0.31	0.462
Crash severity	Binary	Injury crash	0.30	0.456
Driver characteristics				
Driver age	Binary	Young age (age $\leq$ 25 years)	0.25	0.435
		Middle age (age between 25 and 60 years)	0.60	0.491
		Old age (age > 60 years)	0.18	0.384
Alcohol/drugs	Binary	Driver under the influence	0.02	0.151
Hospitalization	Binary	Crash victim hospitalized	0.13	0.332
Crash characteristics				
Manner of collision	Categorical	Non-collision crash	0.14	0.344
		Rear-end crash	0.51	0.500
		Sideswipe crash	0.21	0.410
		Other (head-on, angle, turning)	0.10	0.298
Vehicle type	Binary	Truck or bus	0.06	0.235
Crash type	Binary	Multi-vehicle crash	0.85	0.359
Rescue	Binary	Rescue involved	0.07	0.254
Area designation	Categorical	Industrial district	0.07	0.257
		Business district	0.29	0.452
		Mixed district	0.19	0.391
		Open-area district	0.24	0.426
		Residential/school district	0.20	0.398
Temporal characteristics				
Day of week	Binary	Weekday	0.74	0.440
Time of day	Categorical	AM peak	0.14	0.348
		Midday	0.36	0.481
		PM peak	0.24	0.426
		Night	0.26	0.437
Environmental characteristics				
Lighting conditions	Categorical	Daylight	0.73	0.443
		Dark	0.24	0.424
		Dusk or dawn	0.03	0.167
Weather conditions	Categorical	Clear	0.72	0.448
		Rain	0.12	0.328
		Cloudy	0.14	0.350
		Other weather condition (hail, snow, etc.)	0.01	0.111
Traffic/geometric characteristics				
ADT/1000	Continuous	Average daily traffic	100.90	42.898
Length	Continuous	Segment length (miles)	0.74	0.440

5. Results and Discussions

Fixed-parameter and random-parameter bivariate probit models were estimated using a random sample of 5000 crashes with ICT as the response variable. These models were

analyzed using NLOGIT (version 6) statistical software [34]. Fixed-parameter models were estimated using maximum likelihood methods due to their constant parameters across the dataset, while random-parameter models employed simulated maximum likelihood methods to accommodate the variability in parameters across observations. The random-parameter model was estimated using 1000 Halton draws. The normal distribution was found to provide the best statistical fit for the random parameters.

Table 2 presents the estimated results of the bivariate random-parameter model. Ten variables were found to contribute to the injury severity model. Among these, two variables were found to produce random parameters. For the incident duration model, nine variables were found to be significant, with three producing random parameters. The estimated correlation coefficient between the error terms (p) was estimated at 0.9808, which is statistically significant and shows the existence of common unobserved heterogeneity between injury severity and incident duration.

Table 2. Bivariate random-parameter probit model.

Variable	Injury Severity Model			Incident Clearance Model		
	Coefficient	**Standard Error**	**Z-Score**	**Coefficient**	**Standard Error**	**Z-Score**
Constant	−0.992	0.0557	−17.81	−0.509	0.0720	−7.07
Standard Deviation	*0.763*	*0.0226*	*33.74*	*0.116*	*0.0176*	*6.57*
Driver Characteristics						
Alcohol and/or Drugs Used	0.545	0.1050	5.17	-	-	-
Young Age	0.042	0.0573	0.73	0.131	0.0451	2.90
Standard Deviation	*0.757*	*0.0418*	*18.10*	-	-	-
Middle Age	0.191	0.0453	4.21	-	-	-
Crash Characteristics						
Injury Crash	-	-	-	1.001	0.0611	16.40
Standard Deviation	-	-	-	*1.988*	*0.0832*	*23.89*
Truck-Involved Crash	0.719	0.0820	8.77	0.668	0.0833	8.02
Non-Collision Crash	-	-	-	0.187	0.0698	2.68
Standard Deviation	-	-	-	*1.116*	*0.0639*	*17.47*
Rear-End Crash	0.241	0.0383	6.30	-	-	-
Rescue Involved	1.818	0.0727	25.02	-	-	-
Crash Victims Hospitalized	-	-	-	1.200	0.0816	14.71
Multi-Vehicle Crash	-	-	-	−0.427	0.0642	−6.65
Environmental Characteristics						
Rainy Weather Crash	0.171	0.0533	3.21	-	-	-
Daylight Crash	−0.194	0.0501	−3.87	−0.185	0.0442	−4.18
Area of Crash						
Business District	-	-	-	−0.163	0.0402	−4.04
Temporal Characteristics						
Midday	−0.117	0.0433	−2.70	-	-	-

5.1. Model Comparison

Table 3 shows the model fit statistics of the bivariate fixed-parameter and bivariate random-parameter model. The bivariate random-parameter model has a higher cross-

equation correlation (0.9808) compared to the bivariate fixed-parameter model (0.754). This indicates a better relationship between the estimated parameters in the random-parameter model. A comparison of the two models was also performed using the likelihood ratio test (Equation (4)). The χ^2 statistic is $-2 \times (-5722.33 - [-5534.37]) = 375.92$, which is far greater than the critical threshold of 5.99 (two degrees of freedom). The test shows that the bivariate random-parameter model outperformed the bivariate fixed-parameter model. A lower AIC value typically suggests a better model fit, considering both the goodness of fit and complexity (number of parameters estimated). In this case, the bivariate random-parameter model has a lower AIC (11,119) compared to the bivariate fixed-parameter model (11,498). Given that both models were applied to the same dataset, all statistical estimates suggest that the random-parameter bivariate model provides a superior fit.

Table 3. Performance comparison of fixed- and random-parameter model.

Variable	Bivariate Fixed-Parameter Model	Bivariate Random-Parameter Model
Cross-equation correlation, *p*	0.754	0.9808
Number of parameters	27	25
Log-likelihood at convergence	−5722.33	−5534.65
Akaike information criterion (AIC)	11,498	11,119

5.2. Injury Severity Factors

In terms of driver demographics in this study, unlike prior studies [35,36], young and middle-aged drivers have a higher likelihood of being involved in injury crashes in comparison to older drivers. However, this finding may be accounting for the relatively small number of elderly drivers involved in injury crashes despite their crash risks. Older persons are known to have a smaller rate of licensure and drive fewer miles on average in comparison to other age groups [37]. The results show that the variable for young drivers produced a random parameter with a mean of 0.042 and a standard deviation of 0.757. Given these estimates, the parameter was less than zero for 47.8% of young drivers and greater than zero for 52.2% for young drivers. The implication is that 52.2% of young drivers were more likely to be involved in injury crashes than not. Alcohol and drug use are particularly influential in causing injury crashes on interstates, a finding that aligns with several prior studies [38–40]. Driving under the influence has been consistently identified as a significant risk factor, as the resultant drowsiness from drug and/or alcohol use can diminish driving capabilities, leading to hazardous movement and increased risk for other interstate users [41]. This is further substantiated by Alrejjal et al., who identified drug/alcohol use as one of the main violations significantly influencing crash severity [42].

The involvement of trucks in crashes has been identified as a significant factor contributing to injuries on interstates in this study. Conventionally, collisions involving large trucks on interstates tend to result in more severe injuries [43], primarily due to their substantial size and weight, often 20–30 times that of an average passenger car. Moreover, their elevated height and ground clearance increase the likelihood of a smaller vehicle under-riding the trailer in the event of a crash [44,45]. These findings further indicate a significant association between injury crashes and the presence of rescue units at the crash scene. It is a logical conclusion that the necessity for services like fire departments often aligns with more severe injury crashes.

Rear-end crashes, identified as a significant factor causing injuries on interstates in this study (as presented in Table 3), are among the most prevalent types of incidents on these roads. However, research indicates that rear-end crashes can be particularly severe on urban interstates [35,46]. Chen et al. suggest that the increased severity of crashes on urban interstates may be attributed to high-speed driving [47]. This study recognizes rainy weather as a consequential factor in injury crashes on interstates, a finding that aligns with previous Louisiana studies investigating the impact of inclement weather on

statewide accidents [48,49]. For instance, Rahman et al. found a correlation between rainy weather and both KA and B injury crashes on interstates, particularly those with speed limits exceeding 60 mph and featuring barriers [48]. A plausible reason for these incidents on high-speed interstates might be the inability to maintain a safe speed and sufficient headway for speed adjustments [50].

Rainy weather was found to increase the likelihood of injury crashes. This parameter was fixed across observations. This finding is expected as rainy weather is known to provide challenging driving conditions such as reducing pavement friction, decreasing vehicle stability, and contributing to poor visibility [51]. Conversely, the model results suggest that crashes that occur in daylight have a lower likelihood of being injury crashes. This finding is intuitive as daylight hours provide better visibility and drivers are less likely to be involved in injury crashes in comparison to dark conditions [52]. Similarly, midday crashes were less likely to be associated with injury crashes. This finding is supported by a previous study indicating that the probability of crashes decreases during the midday period [53]. The effects of congestion during the midday period are known to decrease the risk of injury crashes while increasing the probability of non-injury crashes during this period.

5.3. Incident Duration Factors

The bivariate random-parameter logit model indicates that three significant factors, truck involvement, young drivers, and incidents, necessitating hospitalization are positively associated with prolonged incident durations in urban interstate crashes.

A factor that has been identified in the model as increasing incident duration is the involvement of young drivers in crashes. Though many elements can influence the duration of a crash with young drivers, the presence of young drivers could extend it. One possible explanation is that crashes involving young drivers often necessitate more in-depth investigations by law enforcement due to the higher likelihood of these drivers participating in risky behaviors like drinking, speeding, or distracted driving [54,55].

The variable for injury severity produced a random parameter with a mean of 1.001 and a standard deviation of 1.988. Given these estimates, the parameter was less than zero for 30.7% of observations and 69.3% of observations. This implies that for 69.3% of injury crashes, the likelihood of experiencing a longer ICT is increased, while 30.7% of injury crashes are likely to result in a shorter clearance time. As noted in this study previously, the response for injury crashes usually involves multiple agencies and requires more resources in comparison to other crashes. With injury crashes, there may also be a need to carefully move crash victims before attending to them, which could contribute to longer clearance times. For other injury crashes, the strategy of agencies to allocate more resources when injuries are reported may be leading to quicker clearance times of incidents. The increase in labor and equipment may offset the effort and care required to attend to crash victims, thereby leading to shorter ICTs.

Crashes involving trucks extend the duration of incident clearance time on interstates, as supported by several prior studies [16,56]. This parameter was fixed across observations. Trucks, due to their large size and heavy mass, tend to cause more damage when involved in collisions, which naturally necessitates more time for clearance [57,58]. Additionally, incidents such as rollovers/overturns, in addition to being more severe [59], further prolong the clearance time [10,15,60]. This may be because the removal of damaged trucks often involves unique logistical challenges, such as the necessity to disentangle them from other vehicles, tow them away, or even unload their cargo, which can significantly delay the reopening of roadways. Moreover, responding to and clearing truck crashes frequently require coordination among various emergency service entities, leading to extended response and clearance times.

The results also suggest that non-collision crashes lead to longer ICTs on urban interstates. This variable had a random parameter with a mean of 0.187 and a standard deviation of 1.116. The parameter was less than zero for 43.4% of non-collision crashes and

greater than zero for 56.6% of non-collision crashes. The implication is that for the majority of non-collision crashes, there is an increased likelihood of longer ICTs. As noted earlier, this finding may be attributed to the fact that non-collision crashes such as run-off road and overturn crashes are associated with higher crash severities [59]. Also, more effort related to manpower and inter-agency coordination is needed to respond to injury crashes, which may be contributing to longer clearance times. However, for 43.4% of crashes, ICTs are likely to decrease, a finding that may be attributed to the additional resources allocated to injury crashes, which may offset some of the time needed to respond to injuries.

The hospitalization of victims involved in a crash could potentially lengthen the incident duration due to the time required for emergency response and medical procedures [18,61]. This could further depend on the severity and frequency of injuries sustained in the crash, with more severe injuries possibly necessitating longer durations for adequate rescue, emergency care, and response.

Multi-vehicle crashes were associated with shorter ICTs. This finding at first seems counterintuitive, but consideration of this variable's effect in the context of urban interstates makes the result reasonable. The relatively higher traffic volume and congestion associated with urban interstates means crashes are not usually severe when they occur. Though frequent, multi-vehicle crashes in urban areas can quickly be moved to the shoulder of the road, restoring the highway to its original capacity.

The factors that have been negatively associated with incident duration are daylight, business district, and multi-vehicle crashes. During the daytime, the ICT is lower due to the higher visibility compared to the nighttime [62], which enables responders to attend to incidents faster. The business district has been negatively linked to incident duration potentially because of the shorter distance to traffic incident management services including emergency and medical services (EMSs) [18,62]. Contrary to the common perception of multiple vehicle involvement delaying incident response time, this study found that crash incidents with more than one vehicle are negatively associated with incident response time.

6. Conclusions

Incident clearance duration is impacted by several factors including injury severity. The strategy of most transportation agencies is to allocate more resources to injury crashes in comparison to other incidents. The expectation is that such a strategy should result in faster clearance times. However, given that injury crashes require multi-agency collaboration and coordination, care in moving and attending to crash victims, and a greater response effort, injury crashes usually take longer to clear. The implication is that the relationship between injury severity and ICT is complex and not straight forward.

This study contributes to the existing knowledge in the investigation of crash-related incidents and incident duration. The present study identified factors contributing to injury severity and ICT on Louisiana's urban interstates by developing a bivariate probit model. This modeling approach was adopted to investigate unobserved shared heterogeneity between injury severity and ICT. The use of bivariate models results in more efficient estimates when the response variables are inter-related. The results of the analysis confirm that there is statistical significance in the error correlation between the inter-related responses of crash injury severity and ICT. This correlation has been overlooked in previous studies of incident duration analysis. Importantly, the model suggests that ICT is not impacted by injury crashes in only one way. The injury severity variable produced a random parameter, suggesting that some injury crashes result in shorter clearance times, while others increase the clearance duration. Specifically, the results indicate that about 70% of injury crashes increase the likelihood of having longer ICTs, while approximately 30% decrease the probability of longer ICTs. The model results also show the diversity of other factors impacting crash injury severity and ICT on Louisiana's urban interstates. These factors include driver, crash, environmental, and temporal characteristics.

This study provides an in-depth analysis of factors influencing injury severity and ICT on urban interstates, as indicated by strong correlations found in the bivariate models. The

key findings reveal that young and middle-aged drivers are more likely to be involved in injury crashes compared to older drivers, with alcohol and drug use significantly exacerbating the risk, especially among younger demographics. The presence of trucks markedly increases both the severity and duration of incidents due to their substantial size and mass, often requiring extensive clearance efforts. Additionally, environmental conditions such as rainy weather heighten the likelihood of injury crashes by impairing driving conditions.

Notably, rear-end crashes and the timing of incidents (daylight versus nighttime) substantially influence both the severity of injuries and the duration of incident clearance. Daylight hours and multi-vehicle crashes are associated with quicker incident response times, likely due to better visibility and faster roadside assistance. Conversely, incidents during rainy weather or involving impaired drivers result in longer clearance times, emphasizing the challenges of managing urban interstate safety efficiently.

This study provides important knowledge on quantifying the influence of various factors on injury severity and ICT. With this knowledge, an appropriate strategy can be crafted to reduce crash injury severity on Louisiana's urban interstates while improving mobility and the environmental well-being of the state through reduced congestion. A limitation of this study is that it only focused on crash-related severity. Future studies should analyze more incidents with respect to their impact on ICT and safety as more data become available.

Author Contributions: Conceptualization, M.A.R. and M.M.; Methodology, M.A.R. and M.M.; Formal analysis, M.A.R. and M.M.; Investigation, M.A.R.; Data curation, M.A.R.; Writing—original draft, M.A.R., M.M., W.A.K. and J.C.; Supervision, M.M.; Project administration, J.C.; Funding acquisition, J.C. All authors have read and agreed to the published version of the manuscript.

Funding: This study is a complementary work of a research project (SIO No. DOTDLT 1000468) funded by the Louisiana Department of Transportation and Development (DOTD) and was conducted by the Louisiana Transportation Research Center (LTRC).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Data will be available only upon request and with permission from the Louisiana Department of Transportation and Development (DOTD).

Conflicts of Interest: The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

1. Hallenbeck, M.E.; Ishimaru, J.; Nee, J. Measurement of Recurring versus Non-Recurring Congestion. *Dept Transp.* **2003**.
2. Owens, N.; Armstrong, A.; Sullivan, P.; Mitchell, C.; Newton, D.; Brewster, R.; Trego, T. *Traffic Incident Management Handbook*; National Academy of Sciences: Washington, DC, USA, 2010.
3. Blincoe, L.; Miller, T.R.; Wang, J.-S.; Swedler, D.; Coughlin, T.; Lawrence, B.; Guo, F.; Klauer, S.; Dingus, T. *The Economic and Societal Impact of Motor Vehicle Crashes, 2019*; National Highway Traffic Safety Administration: Washington, DC, USA, 2022.
4. NTIMC. *Safe, Quick Clearance: National Unified Goal (NUG) for Traffic Incident Management*; National Traffic Incident Management Coalition: Washington, DC, USA, 2006.
5. O'laughlin, J.; Smith, A. Incident Management Operations: Top Five Issues. Traffic Incident Management A Road Map to the Future. In Proceedings of the TRB Annual Meeting 2002, Irvine, CA, USA, 11 March 2002.
6. U.S. Fire Administration. *Fire Administration Traffic Incident Management Systems*; Federal Emergency Management Agency: Washington, DC, USA, 2012.
7. Dowling, R.G.; Parks, K.L.; Nevers, B.; Josselyn, J.; Gayle, S. *Incorporating Travel-Time Reliability into the Congestion Manage-Ment Process: A Primer*; Federal Highway Administration: Washington, DC, USA, 2015.
8. FHWA. *Travel Time Reliability: Making It There On Time, All The Time*; Federal Highway Administration: Washington, DC, USA, 2017.
9. Alkaabi, A.M.S.; Dissanayake, D.; Bird, R. Analyzing Clearance Time of Urban Traffic Accidents in Abu Dhabi, United Arab Emirates, with Hazard-Based Duration Modeling Method. *Transp. Res. Rec.* **2011**, *2229*, 46–54. [CrossRef]
10. Chung, Y. Development of an Accident Duration Prediction Model on the Korean Freeway Systems. *Accid. Anal. Prev.* **2010**, *42*, 282–289. [CrossRef] [PubMed]
11. Nam, D.; Mannering, F. An Exploratory Hazard-Based Analysis of Highway Incident Duration. *Transp. Res. Part Policy Pract.* **2000**, *34*, 85–102. [CrossRef]

12. Ozbay, K.; Noyan, N. Estimation of Incident Clearance Times Using Bayesian Networks Approach. *Accid. Anal. Prev.* **2006**, *38*, 542–555. [CrossRef] [PubMed]
13. Lee, J.-T.; Fazio, J. Influential Factors in Freeway Crash Response and Clearance Times by Emergency Management Services in Peak Periods. *Traffic Inj. Prev.* **2005**, *6*, 331–339. [CrossRef] [PubMed]
14. Ding, C.; Ma, X.; Wang, Y.; Wang, Y. Exploring the Influential Factors in Incident Clearance Time: Disentangling Causation from Self-Selection Bias. *Accid. Anal. Prev.* **2015**, *85*, 58–65. [CrossRef]
15. Golob, T.F.; Recker, W.W.; Leonard, J.D. An Analysis of the Severity and Incident Duration of Truck-Involved Freeway Accidents. *Accid. Anal. Prev.* **1987**, *19*, 375–395. [CrossRef]
16. Hou, L.; Lao, Y.; Wang, Y.; Zhang, Z.; Zhang, Y.; Li, Z. Time-Varying Effects of Influential Factors on Incident Clearance Time Using a Non-Proportional Hazard-Based Model. *Transp. Res. Part Policy Pract.* **2014**, *63*, 12–24. [CrossRef]
17. Pang, J.; Krathaus, A.; Benedyk, I.; Ahmed, S.S.; Anastasopoulos, P.C. A Temporal Instability Analysis of Environmental Factors Affecting Accident Occurrences during Snow Events: The Random Parameters Hazard-Based Duration Model with Means and Variances Heterogeneity. *Anal. Methods Accid. Res.* **2022**, *34*, 100215. [CrossRef]
18. Tavassoli Hojati, A.; Ferreira, L.; Washington, S.; Charles, P. Hazard Based Models for Freeway Traffic Incident Duration. *Accid. Anal. Prev.* **2013**, *52*, 171–181. [CrossRef] [PubMed]
19. Washington, S.; Karlaftis, M.G.; Mannering, F.; Anastasopoulos, P. *Statistical and Econometric Methods for Transportation Data Analysis*; CRC Press: Boca Raton, FL, USA, 2020; ISBN 0-429-52075-1.
20. Zong, F.; Zhang, H.; Xu, H.; Zhu, X.; Wang, L. Predicting Severity and Duration of Road Traffic Accident. *Math. Probl. Eng.* **2013**, *2013*, e547904. [CrossRef]
21. Arellano, M. Unobserved Heterogeneity. In *Panel Data Econometrics*; Arellano, M., Ed.; Oxford University Press: Oxford, UK, 2003.
22. Baltagi, B.H.; Baltagi, B.H. *Econometric Analysis of Panel Data*; Springer: Berlin/Heidelberg, Germany, 2008.
23. Aidoo, E.N.; Ackaah, W.; Appiah, S.K.; Appiah, E.K.; Addae, J.; Alhassan, H. A Bivariate Probit Analysis of Child Passenger's Sitting Behaviour and Restraint Use in Motor Vehicle. *Accid. Anal. Prev.* **2019**, *129*, 225–229. [CrossRef] [PubMed]
24. Guo, Y.; Zhou, J.; Wu, Y.; Chen, J. Evaluation of Factors Affecting E-Bike Involved Crash and E-Bike License Plate Use in China Using a Bivariate Probit Model. *J. Adv. Transp.* **2017**, *2017*, e2142659. [CrossRef]
25. Lee, J.; Mao, S.; Abdel-Aty, M.; Fu, W. Use of Bivariate Random-Parameter Probit Model to Analyze the Injury Severity of Highway Traffic Crashes Involving School-Age Children. *Transp. Res. Rec.* **2021**, *2675*, 530–537. [CrossRef]
26. Tarko, A.; Azam, M.S. Pedestrian Injury Analysis with Consideration of the Selectivity Bias in Linked Police-Hospital Data. *Accid. Anal. Prev.* **2011**, *43*, 1689–1695. [CrossRef] [PubMed]
27. Greene, W.H.; Hensher, D.A. Ordered Choices and Heterogeneity in Attribute Processing. *J. Transp. Econ. Policy* **2010**, *44*, 331–364.
28. Anastasopoulos, P.C.; Mannering, F.L. An Empirical Assessment of Fixed and Random Parameter Logit Models Using Crash-and Non-Crash-Specific Injury Data. *Accid. Anal. Prev.* **2011**, *43*, 1140–1147. [CrossRef]
29. Lee, J.; Mannering, F. Impact of Roadside Features on the Frequency and Severity of Run-off-Roadway Accidents: An Empirical Analysis. *Accid. Anal. Prev.* **2002**, *34*, 149–161. [CrossRef] [PubMed]
30. Mannering, F.L.; Shankar, V.; Bhat, C.R. Unobserved Heterogeneity and the Statistical Analysis of Highway Accident Data. *Anal. Methods Accid. Res.* **2016**, *11*, 1–16. [CrossRef]
31. Russo, B.J.; Savolainen, P.T.; Schneider, W.H.; Anastasopoulos, P.C. Comparison of Factors Affecting Injury Severity in Angle Collisions by Fault Status Using a Random Parameters Bivariate Ordered Probit Model. *Anal. Methods Accid. Res.* **2014**, *2*, 21–29. [CrossRef]
32. Louisiana DOTD Crash1: Louisiana Highway Crash List. Available online: http://www8.dotd.la.gov/crash1/ (accessed on 5 March 2023).
33. Dunn, W.M.; Latoski, S.P. *Safe and Quick Clearance of Traffic Incidents*; NCHRP Synthesis; Transportation Research Board of the National Academics: Washington, DC, USA, 2003.
34. Econometric Software, Inc. *NLOGIT: Superior Statistical Analysis Software*; Econometric Software, Inc.: Plainview, NY, USA, 2023.
35. Chen, C.; Zhang, G.; Tarefder, R.; Ma, J.; Wei, H.; Guan, H. A Multinomial Logit Model-Bayesian Network Hybrid Approach for Driver Injury Severity Analyses in Rear-End Crashes. *Accid. Anal. Prev.* **2015**, *80*, 76–88. [CrossRef] [PubMed]
36. Chen, C.; Zhang, G.; Tian, Z.; Bogus, S.M.; Yang, Y. Hierarchical Bayesian Random Intercept Model-Based Cross-Level Interaction Decomposition for Truck Driver Injury Severity Investigations. *Accid. Anal. Prev.* **2015**, *85*, 186–198. [CrossRef] [PubMed]
37. Williams, A.F.; Carsten, O. Driver Age and Crash Involvement. *Am. J. Public Health* **1989**, *79*, 326–327. [CrossRef]
38. Chen, C.; Zhang, G.; Huang, H.; Wang, J.; Tarefder, R.A. Examining Driver Injury Severity Outcomes in Rural Non-Interstate Roadway Crashes Using a Hierarchical Ordered Logit Model. *Accid. Anal. Prev.* **2016**, *96*, 79–87. [CrossRef] [PubMed]
39. Chen, C.; Zhang, G.; Liu, X.C.; Ci, Y.; Huang, H.; Ma, J.; Chen, Y.; Guan, H. Driver Injury Severity Outcome Analysis in Rural Interstate Highway Crashes: A Two-Level Bayesian Logistic Regression Interpretation. *Accid. Anal. Prev.* **2016**, *97*, 69–78. [CrossRef] [PubMed]
40. Donnell, E.T.; Mason, J.M. Predicting the Severity of Median-Related Crashes in Pennsylvania by Using Logistic Regression. *Transp. Res. Rec.* **2004**, *1897*, 55–63. [CrossRef]
41. Rahman, M.A.; Das, S.; Sun, X. Understanding the Drowsy Driving Crash Patterns from Correspondence Regression Analysis. *J. Safety Res.* **2023**, *84*, 167–181. [CrossRef]

42. Alrejjal, A.; Moomen, M.; Ksaibati, K. Evaluating the Impact of Traffic Violations on Crash Injury Severity on Wyoming Interstates: An Investigation with a Random Parameters Model with Heterogeneity in Means Approach. *J. Traffic Transp. Eng. Engl. Ed.* **2022**, *9*, 654–665. [CrossRef]
43. Chen, W.-H.; Jovanis, P.P. Method for Identifying Factors Contributing to Driver-Injury Severity in Traffic Crashes. *Transp. Res. Rec.* **2000**, *1717*, 1–9. [CrossRef]
44. Brumbelow, M.L. Potential Benefits of Underride Guards in Large Truck Side Crashes. *Traffic Inj. Prev.* **2012**, *13*, 592–599. [CrossRef] [PubMed]
45. Teoh, E.R.; Carter, D.L.; Smith, S.; McCartt, A.T. Crash Risk Factors for Interstate Large Trucks in North Carolina. *J. Safety Res.* **2017**, *62*, 13–21. [CrossRef] [PubMed]
46. Champahom, T.; Jomnonkwao, S.; Watthanaklang, D.; Karoonsoontawong, A.; Chatpattananan, V.; Ratanavaraha, V. Applying Hierarchical Logistic Models to Compare Urban and Rural Roadway Modeling of Severity of Rear-End Vehicular Crashes. *Accid. Anal. Prev.* **2020**, *141*, 105537. [CrossRef] [PubMed]
47. Chen, C.; Zhang, G.; Yang, J.; Milton, J.C.; Alcántara, A. "Dely" An Explanatory Analysis of Driver Injury Severity in Rear-End Crashes Using a Decision Table/Naïve Bayes (DTNB) Hybrid Classifier. *Accid. Anal. Prev.* **2016**, *90*, 95–107. [CrossRef]
48. Rahman, M.A.; Das, S.; Sun, X. Using Cluster Correspondence Analysis to Explore Rainy Weather Crashes in Louisiana. *Transp. Res. Rec.* **2022**, *2676*, 159–173. [CrossRef]
49. Sun, X.; Hu, H.; Habib, E.; Magri, D. Quantifying Crash Risk under Inclement Weather with Radar Rainfall Data and Matched-Pair Method. *J. Transp. Saf. Secur.* **2011**, *3*, 1–14. [CrossRef]
50. Jung, S.; Jang, K.; Yoon, Y.; Kang, S. Contributing Factors to Vehicle to Vehicle Crash Frequency and Severity under Rainfall. *J. Safety Res.* **2014**, *50*, 1–10. [CrossRef] [PubMed]
51. Kopelias, P.; Papadimitriou, F.; Papandreou, K.; Prevedouros, P. Urban Freeway Crash Analysis: Geometric, Operational, and Weather Effects on Crash Number and Severity. *Transp. Res. Rec.* **2007**, *2015*, 123–131. [CrossRef]
52. Wang, Y.; Zhang, W. Analysis of Roadway and Environmental Factors Affecting Traffic Crash Severities. *Transp. Res. Procedia* **2017**, *25*, 2119–2125. [CrossRef]
53. Khattak, Z.H.; Fontaine, M.D. A Bayesian Modeling Framework for Crash Severity Effects of Active Traffic Management Systems. *Accid. Anal. Prev.* **2020**, *145*, 105544. [CrossRef] [PubMed]
54. Scott-Parker, B.; Bates, L. "They Assume like You Are Doing Something Wrong": Young Drivers and Police. In Proceedings of the 28th International Congress of Applied Psychology, Paris, France, 8–13 July 2014.
55. Tay, R. The Effectiveness of Enforcement and Publicity Campaigns on Serious Crashes Involving Young Male Drivers: Are Drink Driving and Speeding Similar? *Accid. Anal. Prev.* **2005**, *37*, 922–929. [CrossRef]
56. Zeng, Q.; Wang, F.; Chen, T.; Sze, N.N. Incorporating Real-Time Weather Conditions into Analyzing Clearance Time of Freeway Accidents: A Grouped Random Parameters Hazard-Based Duration Model with Time-Varying Covariates. *Anal. Methods Accid. Res.* **2023**, *38*, 100267. [CrossRef]
57. Karlaftis, M.G.; Latoski, S.P.; Richards, N.J.; Sinha, K.C. ITS Impacts on Safety and Traffic Management: An Investigation of Secondary Crash Causes. *ITS J.—Intell. Transp. Syst. J.* **1999**, *5*, 39–52. [CrossRef]
58. Vadlamani, S.; Chen, E.; Ahn, S.; Washington, S. Identifying Large Truck Hot Spots Using Crash Counts and PDOEs. *J. Transp. Eng.* **2011**, *137*, 11–21. [CrossRef]
59. Khattak, A.J.; Schneider, R.J.; Targa, F. Risk Factors in Large Truck Rollovers and Injury Severity: Analysis of Single-Vehicle Collisions. *Transp. Res. Rec.* **2003**, *40*, 1–22.
60. Middleton, D.R. *A Study of Selected Warning Devices for Reducing Truck Speeds*; Texas A&M University: College Station, TX, USA, 1994.
61. Valenti, G.; Lelli, M.; Cucina, D. A Comparative Study of Models for the Incident Duration Prediction. *Eur. Transp. Res. Rev.* **2010**, *2*, 103–111. [CrossRef]
62. Laman, H.; Yasmin, S.; Eluru, N. Joint Modeling of Traffic Incident Duration Components (Reporting, Response, and Clearance Time): A Copula-Based Approach. *Transp. Res. Rec.* **2018**, *2672*, 76–89. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.