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Toll road crash severity using mixed logit model incorporating heterogeneous mean structures

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ABSTRACT
The current study examined 1,465 crash observations (2017–2021) from Louisiana, identifying significant variables grouped into three major categories: drivers', crash, and road characteristics. Considering crash injury severity as a dependent variable, we employed classic Multinomial Logit (MNL) model, and several other models to address unobserved heterogeneity in crash data including Random Parameter Logit (RPL), Random Parameter Logit with Heterogeneity in Means (RPLHM), and Random Parameter Logit with Heterogeneity in Means and Variance (RPLHMV). Our findings highlight the impact of factors such as driver gender, age, traffic violations, driver distractions, crash types, surface conditions, and roadway attributes on crash injury severity. These insights emphasise the complexity of toll road safety and inform targeted interventions to mitigate crash injury severity. Notably, male drivers and those under 25 years old increased property damage likelihood, while factors like driver distractions and lower posted speed limits reduced the likelihood of severe injuries or fatalities.

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Traffic crashes; toll roads; random parameter model; heterogeneity in means; multinomial logit; mixed logit

Introduction

Safety concerns on toll roads are diverse, ranging from traffic congestion and delays at toll booths that can lead to rear-end collisions and driver frustration to issues like incorrect lane usage, electronic toll system errors, and poorly designed toll plazas with visibility problems, especially in adverse weather conditions. These problems can be exacerbated by factors like driver fatigue, maintenance issues, variable posted speed limits, and limited law enforcement, making traditional barrier toll plazas more crash-prone. Addressing these concerns requires a comprehensive approach, including better infrastructure design, maintenance, efficient traffic management, electronic toll systems, and public education campaigns. Toll road safety studies encompass a wide range of topics, including changes in toll lane design, the introduction of Electronic Toll Collection (ETC) systems, shifts from traditional to hybrid toll plazas, disparities in road quality, various funding approaches, industry practices' impact on safety, specific toll plaza configurations, the transition from

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barrier toll plazas to open-road tolling, innovative safety strategies, and investigations into wrong-way driving incidents. Notably, there is a gap in existing research when it comes to analyzing crash severity using toll road-related crash data. While toll-road crashes in Louisiana may not constitute a high number of crashes, their prioritisation is warranted due to the disproportional severity and economic implications associated with these incidents. Note that toll roads serve as critical transportation lifelines, playing a strategic role in facilitating the efficient movement of goods and people. Disruptions on these vital routes can have cascading effects on regional and national transportation networks, underscoring the importance of mitigating risks associated with toll-road crashes.

This study aimed to understand the factors affecting toll road crash outcomes, emphasising the essential assumption that there is variability in both means and variances across different categories of crash severity. Recognising this variability is crucial because it allows for a better assessment of the complex dynamics at play and a more precise identification of the factors contributing to different levels of crash severity on toll roads. In essence, mixed logit modelling empowers transportation safety researchers to comprehensively assess and improve safety on toll roads. Overall, specific research on toll road crashes is critical as it can improve safety on toll roads, reduce economic costs, optimise traffic flow, guide infrastructure planning on toll plaza, inform policies, drive technological advancements, and support data-driven decision making.

Literature review

The unique roadway design and built environment characteristics of toll roads have attracted a lot of research attention in recent times. Several investigations have examined the effects on safety and crash rates resulting from the transition of conventional toll lane designs. Yang, Ozbay, and Bartin (2012) examined the safety effects of Open Road Tolling (ORT) at New Jersey's toll plazas comparing pre-ORT and post-ORT implementation and identified a substantial 24% reduction in crash incidents. Another similar study by Gross et al. (2021) assessed the safety benefits of shifting toll plazas to ORT for the Port Authority of New York and New Jersey and estimated an annual reduction of over 900 crashes and 30 injury-related incidents annually Abuzwidah, Abdel-Aty, and Ahmed (2014) conducted observational studies focusing on the transition to a Hybrid Mainline Toll Plaza (HMTP) setup in Florida and discovered a notable 47% average reduction in total crashes, a 46% decrease in fatal and injury crashes, and a 54% reduction in property damage only crashes. Abuzwidah and Abdel-Aty (2018) analyzed crash data (2007–2013) collected from 100 mainline toll plazas in Florida and identified the safety benefits of Hybrid Toll Plaza (44.7% reduction) and All-Electronic Toll Collection (72.6% reduction) compared to the traditional system. Gordin, Klodzinski, and Dos Santos (2011) conducted a pre–post crash data analysis (2007–2009) on six toll plazas in Florida's Turnpike Enterprise (FTE) system, which had transitioned to Open Road Tolling (ORT) with Electronic Toll Collection (ETC) and found a substantial reduction (70%) in crash occurrences. Chakraborty et al. (2020) examined the safety effects of converting hybrid toll booths in Texas to an AETC system with ORT, using crash data from 2010 to 2015. They discovered that the modification to the AETC system resulted in a significant reduction in total (11.7%), fatal, and injury (20.9%), and property damage only (8.4%) crashes. Yang et al. (2014) evaluated the safety impact of removing toll plazas on the Garden State Parkway in New Jersey highways and discovered a significant

42.1% decrease in total crashes and a 40.1% reduction in crash-related costs after barrier tollbooth removal.

Some of the previous studies focused on the investigation of specific crash types on Toll roads. For example, several studies examined the impact of Wrong Way Driving (WWD) on toll roads in order to identify underlying causes and implement effective solutions to mitigate the problem. Sandt et al. (2019) evaluated the cost-effectiveness of Rectangular Flashing Beacon (RFB) WWD countermeasures on toll road exit ramps in Central Florida. The study found life-cycle benefit–cost ratios ranging from 2.49 to 4.10 for crash-related savings and from 4.77 to 7.20 for savings related to injuries. Rogers, Al-Deek, and Sandt (2014) conducted a comprehensive analysis of WWD incidents on toll roads in Central Florida, utilizing a wide range of data sources such as citations, crash records, and emergency calls. Sandt and Al-Deek (2021) devised a method to assess the potential decrease in fatalities and injuries by implementing advanced countermeasures like RFB and Light Emitting Diode (LED) technologies at exit ramps. Rogers et al. (2016) developed predictive models using WWD citations, 911 calls, and route attributes to identify high-risk areas for WWD accidents in South Florida.

Several studies examined how the utilisation of signs influences a driver and which specific type of sign prompts particular driver behaviours on toll roads. Díaz et al. (2016) used a mobile driving simulator to examine safety concerns related to driver behaviour and toll plaza design, particularly at the Caguas Sur Toll Plaza in Puerto Rico, comparing roadside signage to overhead signage for posted speed limits and lane usage information. According to the study, when subject drivers recognised scenarios with overhead signage, they smoothly changed lanes and slowed down their vehicles as they approached the toll plaza. Valdés et al. (2016) from the University of Puerto Rico at Mayaguez developed a virtual toll plaza simulation to assess electronic toll collection efficiency, safety, and driver behaviour in relation to signage and queues. Misokefalou et al. (2016) examined driver distraction, focusing on external road factors and driver-related variables, conducting experiments on Attica Tollway, Greece to assess the impact of elements like signs and advertisements on driver attention. They found that distractions are independent of driver characteristics including gender, age, and experience and the drivers are more likely to distract from driving task in low traffic conditions. Zeng et al. (2022) proposed a Bayesian spatial generalised ordered probit (SGOP) model incorporating Leroux conditional autoregressive (CAR) prior for the analysis of crash severity. The findings reveal that crash injury severity is influenced by factors such as vehicle type, horizontal curvature, vertical grade, precipitation, visibility, traffic composition, day of the week, crash type, and emergency medical service response time. Chen et al. (2019) identified a substantial influence of pavement condition on injury and non-injury crash occurrences in multi-lane highways. Dong et al. (2016) found geometric design features (such as lane width, the number of left-turn lanes, posted speed limits, and intersection angles) as having statistically significant impacts on both disabling and non-disabling injury crashes. Few investigations have examined various elements within a toll system that may impact the frequency of crashes. Liu, He, and Liu (2020) analyzed real-time social-network data and relevant statistics to investigate the impact of toll-free freeways on traffic crashes, employing sensitivity analysis and developing both statistical regression and neural network prediction models. Swan and Belzer (2013) analyzed crash data and traffic metrics from 2002 to 2006, finding that trucks using alternative routes to avoid tolls on the Ohio Turnpike incurred higher costs per mile due to accidents compared to those using the Turnpike itself. Rephlo et al. (2010) comprehensively evaluated safety concerns near toll collection facilities through diverse methods, yielding valuable insights and safety recommendations for workers and motorists in compliance with SAFETEA-LU legislation.

Review of crash severity models

Crash severity models, like logit or probit models, aim to predict the likelihood of a crash belonging to a specific severity level once it has occurred (Ye and Lord 2011). In crash investigation literature, commonly employed methods include modelling crash severity through unordered (multinomial logit, nested logit, or mixed logit) or ordered (ordered logit or probit) discrete outcome models (Cerwick et al. 2014). According to Savolainen et al. (2011), the predominant models for analyzing traffic crash severity are multinomial logit models and ordered probit models. Meanwhile, the mixed logit models have been widely applied to investigate crash severities (Anastasopoulos and Mannering 2011; Cerwick et al. 2014; Chen and Chen 2011; Haleem and Gan 2013; Kim et al. 2013; 2008; Milton, Shankar, and Mannering 2008; Morgan and Mannering 2011; Savolainen et al. 2011; Ye and Lord 2014). The widespread use of the mixed logit method is attributed to its ability to accommodate individual unobserved heterogeneity by allowing parameters to differ across observations (Chen and Chen 2011), offering more reliable parameter estimates (Cerwick et al. 2014). The choice of a specific model is typically influenced by the data's availability and characteristics (Savolainen et al. 2011). While some researchers opt for nominal models over ordinal ones to avoid constraints on how variables impact ordered discrete outcome probabilities (using the same coefficient for a variable across different crash severities), others favour ordinal models for their simplicity and effective performance, especially in situations with less detailed data (Washington et al. 2020). Penmetsa and Pulugurtha (2018) developed a multinomial logit (MNL) model and estimated odds ratios to explore how road features influence the severity of crash injuries. Yasmin and Eluru (2018) performed empirical analysis utilizing zonal-level crash count data for various crash severity levels in Florida for the year 2015. The outcomes distinctly underscore the superior data fit of the joint model in comparison to the independent model. Ye and Lord (2011) investigated the impact of underreporting on three frequently employed traffic crash severity models: multinomial logit (MNL), ordered probit (OP), and mixed logit (ML) models. They suggested that, to mitigate bias and decrease model variability, fatal crashes should serve as the baseline severity for the MNL and ML models. For OP models, the crash severity rank should be arranged from fatal to property damage only in a descending order. The estimation of crash severity models can be significantly impacted by the size of the sample used (Ye and Lord 2014). Additionally, crash severity models typically employ the maximum-likelihood estimator (MLE), ensuring consistency as sample size increases but lacking efficiency, leading to potential issues in small samples (Washington et al. 2020).

Research gap & study objectives

The literature review reveals a comprehensive array of factors and conditions impacting crash rates in toll road settings. These encompass alterations in toll lane designs, the adoption of ETC systems, shifts from traditional to hybrid toll plazas, disparities in road quality, the effects of specific toll plaza configurations, the transition from barrier toll plazas to open-road tolling, innovative road safety strategies, investigations into WWD incidents, and among other facets. However, there are gaps in research regarding the overall toll system's impact on crash frequency, specific influences of factors like pavement condition and geometric design features, and a comprehensive understanding of safety concerns near toll collection facilities. Addressing these gaps is crucial for a comprehensive understanding of toll road safety and the development of effective interventions.

This study aims to utilise a mixed logit model to explain how diverse array of crash contributing factors influences toll road crash severity outcomes. It operates on the premise that there exists variability in both means and variances across discrete categories of the ordered response variable (e.g. crash severity). In the context of mixed logit modelling, recognising heterogeneity in means and variances signifies that the effects of these factors on crash rates can exhibit substantial variation across different crash scenarios and settings. Consequently, by incorporating this heterogeneity, this study seeks to provide a more complex and advanced analysis capable of capturing the complex interplay between crash contributing factors and their distinct impacts on crash severity classes. Ultimately, this mixed logit approach holds the potential to deliver more precise, robust, and valuable insights for the enhancement of toll road safety.

Methodology

Mixed logit model

In this study, the primary focus is on modelling crash severity at toll roads with discrete outcomes: (i) property damage, (ii) minor or moderate injuries, and (iii) fatal or severe injuries. Prior research on toll roads has employed various methodological approaches. This paper adopts a mixed logit approach with heterogeneity in means and variances to assess the relationship between crash severity and factors potentially impacting it on toll roads. To apply this model, the first step involves defining a function for determining toll road crash severity levels (Washington et al. 2020) as,

$$S_{ij} = \boldsymbol{\beta}_i \boldsymbol{X}_{ij} + \varepsilon_{ij} \tag{1}$$

where S_{ij} is injury severity function that determines severity level i of crash j that occurred at a toll road. $\boldsymbol{X}_{ij}$ contain independent variables that affect crash severity level i, $\boldsymbol{\beta}_i$ is a vector of estimable parameters, and ε_{ij} represent the error term which is assumed to follow a generalised extreme value distribution. To allow the possibility of any independent parameter varying across the vector $\boldsymbol{\beta}_i$, a mixed logit model result as (McFadden and Train 2000):

$$P_j(i) = \int \frac{EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{ij})}{\sum_{\forall I} EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{ij})} f(\beta|\varphi) d\beta \tag{2}$$

where $f(\beta|\varphi)$ refers to the density function or distribution of β, φ denotes the vector of parameters associated with the density function in question and $P_j(i)$ is the likelihood that crash j will result in crash severity level i. To account for unobserved heterogeneity in the means and variances of the random parameters, Equation (1) is modified. This modification allows for the vector of estimable parameters $\boldsymbol{\beta}_{ij}$ to change across crashes defined as (Islam and Mannering 2020; Mannering, Shankar, and Bhat 2016):

$$\boldsymbol{\beta}_{ij} = \beta_i + \boldsymbol{\Theta}_{ij}\boldsymbol{Z}_{ij} + \boldsymbol{\sigma}_{ij}EXP(\psi_{ij}\boldsymbol{Y}_{ij})\upsilon_{ij} \tag{3}$$

where the mean parameter β_i is estimated across all incidents, the vector $\boldsymbol{Z}_{ij}$ includes parameters that captures heterogeneity in the means that affect crash severity level i, $\boldsymbol{\Theta}_{ij}$ is a corresponding vector of estimable parameters. Equation (3) implies that$\beta_i + \boldsymbol{\Theta}_{ij}\boldsymbol{Z}_{ij}$ comprises the mean and its heterogeneity. In the Random Parameter Logit (RPL) model, the focus is on estimating the mean effect β_i, while in the Random Parameter Logit with Heterogeneity in Means (RPLHM) model, the additional term $\boldsymbol{\Theta}_{ij}\boldsymbol{Z}_{ij}$ accounts for the heterogeneity in means, allowing for variation in the effect based on $\boldsymbol{Z}_{ij}$ values. $\boldsymbol{Y}_{ij}$ represents factors capturing heterogeneity in the standard deviation $\boldsymbol{\sigma}_{ij}$ with corresponding parameter vector ψ_{ij} and υ_{ij} is a disturbance term.

The random parameters were modelled while assuming that random terms are following the normal distribution. Model estimations employed 1000 Halton draws for simulated maximum likelihoods (Bhat 2001; McFadden and Train 2000; Train 2009; Washington et al. 2020). Finally, to determine the influence of parameters on crash severity outcomes at toll roads, marginal effect (ME) estimates were computed from the best model (RPLHM) to provide insights into the specific effects of significant factors.

To determine which among the standard multinomial logit model, the random parameter logit model, or the random parameter logit model with heterogeneity in means offers the most suitable structure for modelling crash severities at toll roads, we applied the likelihood ratio test (Watson and Westin 1975) to compare the goodness of fit of these models. The test relies on the log-likelihood ratio (LR):

$$LR = -2(L_R - L_U) \tag{4}$$

Where L_U is the log-likelihood of the unrestricted model and L_R is the log-likelihood of the restricted model.

Data collection and preparation

We collected five years (2017–2021) of traffic crash data from Louisiana. Using the filter 'HWY_TYPE_CD = G = Toll Road,' it is found that 1,465 crashes occurred on toll roadways in Louisiana. Table 1 presents a breakdown of traffic crash counts by severity using the KABCO scale for the years 2017–2021, along with a total count for each severity level over this five-year span. The KABCO scale categorises crashes into five injury levels: K (Fatal), A (Incapacitating Injury), B (Non-Incapacitating Injury), C (Possible Injury), and O (Property Damage Only). Notably, there were 10 fatal crashes recorded during this period. Incapacitating injury crashes accounted for 20 cases, followed by 133 non-incapacitating injury crashes, 338 possible injury crashes, and the most numerous, 964 property damage only crashes. The total crash count shows a slight decline of toll roadway crashes since 2018. As exposure of toll roads are not readily available, we can't confirm crash rate declination in the recent years.

In this study, we collected data from 1,465 observations across various categories. Table 2 presents the descriptive statistics for the key variables. The significant parameters are categorised into driver characteristics, crash characteristics, roadway characteristics, and vehicle

Table 1. Toll road crashes by year and crash severity.

Year	K	A	B	C	O	Total
2017	2	0	43	71	265	381
2018	4	4	28	54	256	346
2019	4	14	13	57	205	293
2020	0	0	15	71	119	205
2021	0	2	34	85	119	240
Total	10	20	133	338	964	1465

Table 2. Descriptive statistics of key explanatory variables.

Variable	Mean	Std. dev.
Response variable		
Injury severity	0.333	0.471
Driver characteristics		
Gender (0 if driver was female; 1 if driver was male)	0.678	0.467
Young driver (1 if drivers age was less than 25; 0 otherwise)	0.478	0.500
Driver aged 25–45 years old (1 if yes; 0 otherwise)	0.116	0.320
Prior contribution or primary contributing factor (1 if driver had a violation; 0 otherwise)	0.768	0.422
Distraction (0 if the driver was normal; 1 if driver was distracted)	0.357	0.479
Occupant's number (0 if single occupant; 1 otherwise)	0.906	0.291
Prior movement (0 if driver was moving straight;1 if driver slowing to stop or stopped)	0.350	0.477
Crash characteristics		
Rear end collision (1 if crash type was rear end; 0 otherwise)	0.631	0.483
Sideswipe (1 if it was a sideswipe collision; 0 otherwise)	0.154	0.361
Surface (1 if road surface was wet; 0 if it was dry)	0.202	0.401
Daylight (1 if crash happened during daylight; 0 otherwise)	0.773	0.419
Roadway characteristics		
PSL [$<$ 45] (1 if the posted speed limit was less than 45 mph; 0 otherwise)	0.181	0.385
PSL [50–60] (1 if the posted speed limit was between 50 and 60 mph; 0 otherwise)	0.067	0.250
PSL [$>$ 60] (1 if the posted speed limit was greater than 60 mph; 0 otherwise)	0.752	0.432
Darkness (1 if the crash happened in darkness with no streetlight; 0 otherwise)	0.135	0.341
Vehicle type		
Car (1 if the vehicle was a car; 0 otherwise)	0.361	0.480
SUV (1 if the vehicle was a SUV; 0 otherwise)	0.273	0.445

type. These variables are also used as significant variables by other studies to model crash severity. To address unobserved heterogeneity in crash severity modelling, a commonly employed method involves categorising crash records into homogeneous groups based on various attributes (e.g. driver age, gender, or crash type) (Chang et al. 2021). Chang et al. (2021) also considered key explanatory variable groups such as crash characteristics, roadway features, lightening conditions, and vehicle type in their crash severity model. Separate crash injury severity models are then estimated for each group, known as the exogenous segmentation-based approach and found these variables to be significant in crash injury severity. Pai and Saleh (2008) examined the severity of injuries resulting from crashes involving various collision types, including head-on, sideswipe, rear-end, approach-turn, both-turning, and angle incidents.

In this study, all the independent parameters are represented as indicator variables. The indicator variables were coded into binary format (1 or 0). The coding scheme of indicator variables were based on engineering judgement. Our response variable encompasses three levels of crash severity: Property damage only (PDO), minor or moderate injuries (BC), and fatal or severe injuries (KA).

Results and discussions

In the context of assessing the relationship between crash severity and influencing factors on toll roads, the adoption of RPL, RPLHM, and RPLHMV models proves essential. Toll road environments inherently exhibit diverse conditions and user characteristics, leading to unobserved heterogeneity. The RPL model addresses this by incorporating random parameters to capture variations in parameters affecting crash severity on toll roads. Transitioning to RPLHM introduces flexibility, accommodating variability in random parameters, crucial for representing the dynamic nature of toll road conditions. Capturing both means and variances of random parameters is addressed by the RPLHMV model, providing a comprehensive understanding of crash severity variations within and across driver groups. These models enhance the study's analytical capabilities, offering an innovative approach to better comprehend the complex relationship between contributing factors and crash severity outcomes on toll roads. The backward elimination method was employed in developing the Multinomial Logit (MNL) model. Consequently, certain variables, such as 'Driver aged 25–45 years old' as depicted in Table 2, were excluded from the model due to their lack of statistical significance. The foundational MNL model derived through backward elimination served as the basis for constructing the RPL model. To develop RPL model, we conducted randomness tests on all model parameters. We systematically tested all parameters to identify those with statistically significant estimated means and scales, as these candidates are potential contributors to mixed logit models. The aim is to discern which parameters exhibit significant variability, indicative of their potential to influence the model. Subsequently, various combinations of these significant random parameters are tested to identify the optimal mixed logit model. After testing all parameters in the model for the RPL model, it was determined that the prior contribution or primary contributing factor stood out as the most suitable candidate for a random parameter. To account for unobserved heterogeneity in crash data, we introduced the RPLHM. We examined all parameters in the dataset to pinpoint factors influencing the mean of random parameters. After a comprehensive investigation, we discovered that rearend collisions have a statistically significant impact on the mean of drivers' violations in relation to the 'prior contribution or primary contributing factor' variable. The same process was employed to explore heterogeneity in variance, seeking parameters that could influence the variability or scale of random parameters. No variable had a significant impact on the variance of the random parameter; consequently, the data did not conform to the RPLHMV. To substantiate this, the outcomes of testing all parameters in the dataset to unveil unobserved heteroscedasticity in means and variances have been recorded in Appendix Table A1. The table delineates the influence of each parameter in the data on the variance of random parameters. Each row represents the effect of a particular variable on the variance of random parameters in an individual model. For our modelling work, we utilised the NLOGIT programme, and the model results are presented in Table 3. The outcomes suggest that the RPLHM model performed better than the other models. Additionally, NLOGIT provided us with values for the likelihood function, AIC, and AIC/N, McFadden Pseudo R-squared, which are crucial for evaluating the model's goodness of fit, and these values are reported in Table 3. Employing the likelihood ratio test to compare the final models and assess their goodness of fit, the results from the likelihood ratio test in Equation 4 indicate a high level of confidence (99.99%) that the Random Parameter Logit RPL model is statistically superior to the Multinomial Logit (MNL) model. Additionally, the RPLHM model is found to be statistically superior to the RPL model, as suggested by separate test results.

For a more comprehensive understanding, we also examined the marginal effects of the RPLHM model, which is presented in Table 4. To assess the impact and direction of variables on different levels of crash injury severity in the best model, RPLHM, marginal effects are calculated for each severity level. These effects represent the actual change in the probability of each injury severity level when a parameter value increases by one unit. Specifically, for indicator parameters, the effects are computed as the difference in estimated probabilities. A negative sign signifies a reduction in the probability of injury severity, whereas a positive sign indicates an increase in probabilities (Washington et al. 2020).

Driver characteristics

Driver gender

This parameter consistently demonstrated significance across all models, featuring a positive coefficient. In the RPLHM model, identified as the best-fit model, the estimated positive coefficient for this variable stands at 0.857 for PDO crashes, as detailed in Table 3. This suggests that male drivers are expected to increase the likelihood of property damage. The marginal effects analysis presented in Table 4 sheds light on the variable's influence across different injury severity levels. Specifically, male drivers increased the likelihood of property damage by 0.083, while the likelihood of involvement in fatal or severe injuries decreased by 0.011 for male drivers. Furthermore, the likelihood of moderate or minor injuries decreased by 0.073 for male drivers. Indeed, this implies that male drivers are more likely to be involved in crashes resulting in property damages, while it is less likely for crashes involving male drivers to lead to moderate, minor, or serious injuries. This is in line with a previous study which also identified male drivers as safer on toll roads (Abdelwahab and Abdel-Aty 2002).

Young driver (Driver's age less than 25 years)

The variable portrays significant influence in all three models. The estimated positive coefficient in the RPLHM model is 0.372 for PDO crashes as reported in Table 3. The positive coefficient indicates that drivers who are younger than 25 years are more likely to get involved in crashes that result in property damage. The marginal effects reported in Table 4 show that the likelihood of young drivers being involved in crashes that result in property damage increased by 0.026. Also, for these drivers, the likelihood of minor or moderate injuries decreased by 0.023, and 0.003 for fatal or severe injuries. Overall, young drivers are more likely to be involved in crashes that result in property damage than minor to moderate injuries, and less likely to be involved in crashes that result in fatalities or severe injuries. Although young drivers are usually characterised by their inexperience and risk-taking behaviours, their involvement in crashes on toll roads was found to result in property damage crashes due to the unique settings, and traffic control.

Prior contribution or primary contributing factor

This variable is also significant throughout all models. This variable negatively influences the likelihood of being involved in minor or moderate injuries if the driver has any traffic violation. In the RPLHM model, the estimated coefficient is −1.461 meaning that the likelihood of minor or moderate injuries is lowered for drivers who had a prior violation of rules.

Table 3. Model estimates.

	MNL			RPL			RPLHM		
Variable	Coeff	*t*-stat	*p*-value	Coeff	*t*-stat	*p*-value	Coeff	*t*-stat	*p*-value
Driver characteristics									
[PDO]Gender (0 if driver was female; 1 if driver was male)	0.630	5.76	.0000***	0.850	5.37	.0000***	0.857	5.3	.0000***
[PDO]Young driver (1 if drivers age was less than 25; 0 otherwise)	0.286	2.61	.0092***	0.354	2.54	.0110**	0.372	2.48	.0133**
[BC]Prior contribution (1 if driver had a violation; 0 otherwise)	−0.328	−2.62	.0088***	−0.574	−2.48	.0131**	−1.461	−2.69	.0071***
St. dev. of prior contribution	–	–	–	1.700	2.71	.0067***	2.306	2.85	.0043***
[KA]Distraction (0 if the driver was normal; 1 if driver was distracted)	−1.047	−2.56	.0105**	−1.191	−3	.0027***	−1.083	−2.72	.0064***
[KA]Occupant's number (0 if single occupant; 1 otherwise)	−0.625	−1.84	.0655*	–	–	–	–	–	–
[KA]Prior movement (0 if driver was moving straight; 1 if driver slowing to stop or stopped)	−1.610	−2.89	.0038***	−1.894	−3.53	.0004***	−1.674	−3.15	.0017***
Crash characteristics									
[PDO]Rear-end collision (1 if crash type was rear-end; 0 otherwise)	−0.275	−2.2	.0280**	−0.317	−2.08	.0376**	–	–	–
[BC]Sideswipe (1 if it was a sideswipe collision; 0 otherwise)	−0.859	−4.29	.0000***	−1.088	−3.92	.0001***	−0.907	−3.1	.0020***
[BC]Surface (1 if road surface was wet; 0 if it was dry)	−0.719	−4.72	.0000***	−0.868	−4.24	.0000***	−0.869	−3.98	.0001***
[KA]Daylight (1 if crash happened during daylight; 0 otherwise)	−1.323	−3.93	.0001***	−1.544	−5.28	.0000***	−1.448	−4.89	.0000***
Roadway characteristics									
[KA]PSL [$<$ 45] (1 if the posted speed limit was less than 45 mph; 0 otherwise)	−1.603	−2.18	.0296**	−1.778	−2.43	.0150**	−1.797	−2.46	.0140**
[BC]PSL [$>$ 60] (1 if the posted speed limit was greater than 60 mph; 0 otherwise)	0.225	1.9	.0578*	0.354	2.26	.0241**	0.481	2.83	.0046***
[BC]Dark with no lighting (1 if the crash happened in darkness with no streetlight; 0 otherwise)	0.380	2.32	.0204**	0.441	2.13	.0335**	0.470	2.1	.0357**
Vehicle type									
[KA]Car (1 if the vehicle was a car; 0 otherwise)	−1.216	−2.98	.0029***	−1.442	−3.69	.0002***	−1.398	−3.57	.0004***
[KA]SUV (1 if the vehicle was a SUV; 0 otherwise)	−1.098	−2.39	.0170**	−1.328	−2.96	.0030***	−1.261	−2.8	.0051***
Heterogeneity in means of random parameter									
The effect of rear-end crashes on mean of random parameter prior contribution	–	–	–	–	–	–	1.116	2.73	.0063***

(*continued*).

Table 3. Continued.

Variable	MNL			RPL			RPLHM		
	Coeff	*t*-stat	*p*-value	Coeff	*t*-stat	*p*-value	Coeff	*t*-stat	*p*-value
Statistics									
Number of observations					1464				
Log Likelihood		−1010.519			−1010.223			−1004.778	
McFadden Pseudo *R*-squared		–			0.372			0.375	
AIC		2051			2050.4			2039.6	
AIC/N		1.401			1.401			1.393	

***, **, * = = > Significance at 1%, 5%, 10% level.

Table 4. Marginal effects of the significant variables for the best model RPOPHM.

Variable	PDO	BC	KA
Driver characteristics			
Gender (0 if driver was female; 1 if driver was male)	0.083	−0.073	−0.011
Young driver (1 if drivers age was less than 25; 0 otherwise)	0.026	−0.023	−0.003
Prior contribution (1 if driver had a violation; 0 otherwise)	−0.015	0.015	0.000
Distraction (0 if the driver was normal; 1 if driver was distracted)	0.004	0.001	−0.006
Prior movement (0 if driver was moving straight; 1 if driver slowing to stop or stopped)	0.003	0.001	−0.004
Crash characteristics			
Sideswipe (1 if it was a sideswipe collision; 0 otherwise)	0.013	−0.014	0.001
Surface (1 if road surface was wet; 0 if it was dry)	0.020	−0.021	0.001
Daylight (1 if crash happened during daylight; 0 otherwise)	0.013	0.004	−0.017
Roadway characteristics			
PSL [< 45] (1 if the posted speed limit was greater than 45 mph; 0 otherwise)	0.002	0.000	−0.002
PSL [> 60] (1 if the posted speed limit was greater than 60 mph; 0 otherwise)	−0.049	0.051	−0.002
Dark with no lighting (1 if the crash happened in darkness with no streetlight; 0 otherwise)	−0.009	0.010	−0.001
Vehicle type			
Car (1 if the vehicle was a car; 0 otherwise)	0.005	0.002	−0.007
SUV (1 if the vehicle was a SUV; 0 otherwise)	0.004	0.001	−0.005

This parameter was identified as a random variable with a mean of −1.461 and a standard deviation of 2.306. To gain insights into the distributional splits of the random parameters across respondents, a distributional calculator is employed. The estimated coefficient and scale of the ‘Prior contribution or primary contributing factor’ serve as the mean and standard deviation parameters in this distributional calculation. To discern the distribution split around 0, the objective is to identify the area above or below this central point. Utilizing this approach, the analysis reveals that 73.68% of the cases involving drivers who violated traffic rules, the probability of experiencing minor or moderate injuries decreased, while in 26.32% of these cases, the likelihood of such injuries increased. Based on the marginal effect results reported in Table 4, it is evident that the likelihood of moderate or minor injuries increased by −0.015 for traffic violators. This violation may be attributed to excessive speeding, and it is consistent with findings from a previous study (Alrejjal, Moomen, and Ksaibati 2022). The likelihood of property damage decreased by 0.015 among this group. Furthermore, the data also indicates that the likelihood of experiencing fatal or severe injuries stayed the same. These findings offer valuable insights into the impacts of traffic rule violations, with a slight trade-off between injuries and property damage, and a minimal reduction in the risk of severe injuries.

Driver distraction

The variable 'driver distraction' is also found significant across all models. The parameter 'distraction' has a negative influence on the occurrence of fatal or severe injuries. The coefficient of −1.083 in the RPLHM model (see Table 3) denotes that the likelihood of being involved in fatal or severe injuries is reduced for the driver who was distracted. Further analysis in Table 4 shows that a distracted driver has a 0.006 lower likelihood of being involved in fatal or severe injuries. On the contrary, the likelihood of being involved in minor or moderate injuries increased by 0.001, and for property damage, it increased by 0.004. In summary, distracted drivers are more likely to be involved in crashes resulting in property damage, while the likelihood of these crashes resulting in fatal or severe injuries is lowered. However, the common intuition about distracted drivers who are more likely to be fatally and severely injured (78.6%) (Wu et al. 2014), distracted drivers may attempt to compensate for their errors in driving by speed reduction or increased following distance (Young, Regan, and Hammer 2007) which may result in less severe crashes on toll roads.

Number of occupants in the vehicle

This variable is significant for only the MNL model. It has a negative coefficient on fatal or severe injury as reported in Table 3. The coefficient −0.625 indicates that a vehicle having multiple occupants reduces the likelihood of fatal or severe injury. Although the relationship between the number of occupants in a vehicle and driving behaviour is complicated, a previous study suggests that drivers tend to display safer driving behaviour when they are accompanied by passengers and more passengers lowers the likelihood of severe crash due to positive interaction among themselves (Lee and Abdel-Aty 2008). Overall, the number of occupants has a positive effect on driver's crash involvement on toll roads.

Prior movement

This variable is significant across all models with a negative coefficient. The negative coefficient presented in Table 3 signifies that vehicles exhibiting a tendency to slow down or come to a complete stop are less likely to be involved in fatal injuries or incurring severe injuries. In Table 4, the marginal effect of fatal or severe injuries is −0.004, indicating that vehicles with a prior pattern of slowing down or stopping are 0.004 less likely to experience fatal or severe injuries. However, the probability of such vehicles being involved in crashes resulting in minor or moderate injuries increased by 0.001 and this likelihood also rose for crashes resulting in property damage, by 0.003. Overall, it is more likely for drivers who slowed down to stop or stopped in crashes to result in property damage than in minor or moderate injuries. Conversely, it is less likely for these crashes to result in fatal or severe injuries. This is consistent with a previous study that also highlighted that the vehicles having a tendency to slow down are less involved in fatal or severe injuries whereas the likelihood for property damage crashes remains higher (Li et al. 2019).

Crash characteristics

Rear-end collision

The 'rear-end crashes' indicator displayed statistical significance solely in the MNL and RPL models, as indicated in Table 3. In both models, the presence of a negative coefficient implies that rear-end collisions are associated with a reduced likelihood of more severe crashes. Notably, this variable did not exhibit a significant impact on crash severity in the RPLHM model, and the marginal effect was not computed for this variable in the context of the RPLHM model. The reduced likelihood of severe injury in rear-end collisions is consistent with previous research (Khattak 2001). The intuitive nature of rear-end collision is that the striking vehicle travels at a lower speed than the vehicle it is hitting. The difference in relative speeds can mitigate the severity of the impact. Generally, vehicles are designed in such a way that they deform and absorb energy during a rear-end collision, which reduces the likelihood of severe crashes.

Sideswipe collision

This variable exhibited significance across all the models with a negative coefficient, as shown in Table 3. It exerts a negative influence on the likelihood of being involved in minor or moderate injuries when a sideswipe collision occurs. In the RPLHM model, specifically, the estimated coefficient is – 0.907, indicating that the occurrence of a sideswipe collision lowers the likelihood of experiencing minor or moderate injuries. Additional examination in Table 4 reveals that when a sideswipe collision occurs, there is a 0.013 higher likelihood of property damage and a minimal 0.001increase in the likelihood of fatal or severe injuries. Conversely, this type of collision results in a 0.014 reduction in the likelihood of minor or moderate injuries. Overall, sideswipe collisions are more likely to result in property damage than fatal or severe injuries, and less likely to lead to minor or moderate injuries. While approaching to toll plaza, a driver usually merges to decide which lane to enter and can be a potential source of sideswipe collisions on toll roads (Mohamed, Abdel-Aty, and Klodzinski 2001). The driver's involvement in such sideswipe collision is expected to result in less severe crashes because vehicles generally make contact along their sides and result in less damage to the vehicle.

Surface condition

The 'surface' indicator displayed statistical significance across all the models, as shown in Table 3. It shows a negative influence (coefficient $= -0.869$) on the likelihood of being involved in minor or moderate injuries when a collision occurs on wet roads. Table 4 reveals that when a collision occurs on a wet surface, there is a 0.02 higher likelihood of property damage and a minimal 0.001 increase in the likelihood of fatal or severe injuries. On the contrary, this type of collision results in a 0.021 reduction in the likelihood of minor or moderate injuries. Overall, crashes that occur on wet roads are more likely to result in property damage while it is less likely for them to result in minor or moderate injuries. In previous studies, wet road surfaces were associated with a decrease in the likelihood of fatal injury and incapacitating injuries and an increase in property damage likelihood. This behaviour means that drivers tend to adjust their speeds on wet roads, a form of risk compensation behaviour aimed at lowering perceived driving risk (Li et al. 2019).

Daylight

This variable shows significance across all the models, as shown in Table 3. It exerts a negative influence on the likelihood of being involved in fatal or severe injuries when a collision occurs during daytime with a coefficient of -1.488. Table 4 reveals that when a collision occurs during daytime, there is a 0.013 increase in the likelihood of property damage and a minimum 0.004 increase in the likelihood of minor or moderate injuries. Conversely, this type of collision results in a 0.017 reduction in the likelihood of fatal or severe injuries. Overall, crashes occurring during daylight are more likely to result in property damage, and it is less likely for these crashes to lead to fatal or severe injuries. Due to the improved visibility in daylight conditions, drivers are more likely to react quickly to different traffic maneuvres (e.g. merging or diverging) and avoid potential crashes on toll roads. Previous research suggests that the fixed parameter related to lighting conditions indicates a lower likelihood of fatal or major injury crashes but a comparatively higher likelihood of minor injury crashes occurring during daylight (Shaheed et al. 2013).

Roadway characteristics

PSL less than 45 mph

The estimated coefficient of this parameter is −1.797 as reported in Table 3. The negative sign indicates that the likelihood of fatal or severe injuries decreased in the areas where the posted speed limit was less than 45 mph. This negative relation is likely to be a consequence of a lower speed limit. Drivers travelling at lower speeds have more allowance in time to react and take evasive action in the event of a crash thus reducing injury severity. The marginal effects in Table 4 highlighted that the probability of fatal or severe injuries was decreased by 0.002 for the crashes that happened in these areas. Also, the likelihood of minor or moderate injuries stayed the same while the likelihood of property damages increased by 0.002. Overall, crashes that occur in areas with a posted speed limit of less than 45 mph are more likely to result in property damage, and it is less likely for these crashes to lead to fatal or severe injuries. Supporting this, a previous study reveals that marginal effects indicate an increased likelihood of possible minor injury crashes when the posted speed limit is less than 45 mph. Conversely, when the speed limit is greater than 45 mph, the likelihood of fatal or severe injury crashes increases (Wang et al. 2021).

PSL greater than 60 mph

In the context of areas with a posted speed limit exceeding 60 mph, the analysis from Table 3 reveals that the likelihood of minor or moderate injuries increases (coefficient = 0.481). Marginal effects presented in Table 4 further elucidate the impact of these areas, indicating a substantial 0.051 rise in the probability of minor or moderate injuries for crashes occurring in such zones. This notable increase can be attributed to the higher speeds typically associated with these areas. When vehicles travel at higher speeds, collisions can result in more severe impacts, heightening the probability of individuals sustaining minor or moderate injuries, even if the crashes are non-fatal. The converse effect is observed for property damage, with a decrease of 0.049in likelihood. Moreover, the probability of fatal or severe injuries slightly decreased by 0.002 in these areas. Overall, it is more likely for crashes occurring in areas with a posted speed limit exceeding 60 mph to result in minor or moderate injuries.

Dark with no lighting

The absence of streetlights is linked to an increased likelihood of minor or moderate injuries in nighttime crashes without streetlights, as indicated by the positive coefficient (0.470) in Table 3. The marginal effect results in Table 4 show that this increase is approximately 0.01. Conversely, the absence of streetlights decreased the likelihood of property damage by about 0.009, which could be attributed to the lower density of property in areas without streetlights. Additionally, the probability of fatal or severe crashes decreased by 0.001, possibly due to heightened caution among drivers in dark conditions. In summary, crashes occurring in darkness without streetlights are more likely to result in minor or moderate injuries, and it is less likely for these crashes to lead to property damage. As per the earlier investigation, crashes due to darkness are more prone to result in minor and severe injuries, with a lower likelihood of causing moderate injuries (Islam et al. 2023).

Vehicle type

Car

The indicator variable consistently displayed a negative sign across all models. In our most robust model, the RPOPHM model, this variable showed a coefficient of − 1.398, as documented in Table 3. This negative coefficient implies that the presence of the variable 'car' was associated with a heightened likelihood of cars being involved in fatal or severe crashes, indicating that they were more prone to such serious crashes. Digging deeper into the data presented in Table 4, which reports marginal effects, we uncover a more nuanced impact of the 'car' variable on various outcomes. Specifically, it increased the likelihood of property damage by 0.005 and minor to moderate injuries by 0.002. However, notably, this likelihood decreased by 0.007 when it came to fatal or severe injuries. Overall, crashes involving cars are more likely to result in property damage rather than minor or moderate injuries, and these crashes are less likely to result in fatal or severe injuries. Supporting this, a prior study indicates that the probability of potential minor or moderate injury crashes increases for car users. Conversely, the probability of fatal or severe injury decreased (Obaid et al. 2023).

SUV

This variable exhibits a negative sign with a coefficient of − 1.261 (see Table 3). This implies that the presence of the 'SUV' vehicle type is associated with a reduced likelihood of being involved in fatal or severe crashes. To assess the magnitude of this effect, Table 4 reports the marginal effects of SUVs, indicating slight increases in the likelihood of property damage and minor to moderate injuries by 0.004 and 0.001, respectively. Conversely, this probability decreases by 0.005 for fatal or severe injuries. This complex pattern may be attributed to the larger size of SUVs, which leads drivers to exercise greater caution due to the increased potential for severe outcomes in collisions, potentially resulting in more property damage. This is also consistent with previous research (Razi-Ardakani, Mahmoudzadeh, and Kermanshah 2019). Overall, crashes involving SUVs are more likely to result in property damage rather than minor or moderate injuries, and these crashes are less likely to lead to fatal or severe crashes.

Heterogeneity in means of the random parameters

All variables within the dataset underwent examination to account for unobserved variations in means. Among the various variables, 'Prior contribution' was identified as a random parameter influenced by a specific crash type 'rear-end collisions.' The indicator variable 'rear-end collisions' positively influenced the mean of the random parameter, with a coefficient of 1.116, as detailed in Table 3. Rear-end crashes caused an increase in the mean of random parameters, prior contribution to crash = violation. This implies that in locations where rear-end collisions occurred, drivers were more likely to have violated traffic rules (e.g. disregarding traffic signals, instructions, speeding). The over-representation of rear-end collisions on toll roads is well-established in previous research, especially in the upstream segment of the toll plaza (Abuzwidah and Abdel-Aty 2015; Abuzwidah, Abdel-Aty, and Ahmed 2014; Ardekani 1991; Ding, Ye, and Lu 2008; Mohamed, Abdel-Aty, and Klodzinski 2001; Xing et al. 2020). Drivers may focus on choosing a lane while not paying attention to the front vehicles and stopping suddenly resulting in rear-end collision.

Conclusions and future direction

In this study, our primary goal was to delve into the multitude of factors influencing the severity of toll road crashes, utilizing a crash dataset collected from Louisiana encompassing 1,465 observations (2017–2021) across diverse variable categories. The significant parameters were thoughtfully categorised into four key domains: driver characteristics, crash characteristics, roadway characteristics, and vehicle type. Our response variable dissected crash severity into three distinct tiers: Property damage only (PDO), minor or moderate injuries (BC), and fatal or severe injuries (KA). To unlock the inherent intricacies of our data, we harnessed the power of the Multinomial Logit (MNL) model and its variants, including RPL, and RPLHM models. There was no significant RPLHMV model that fit the data and influenced the variance of random parameters. Employing the NLOGIT programme, we meticulously evaluated model performance metrics, including the likelihood function value, AIC, and AIC/N, McFadden Pseudo R-squared, establishing the RPLHM model as the most adept choice for our dataset.

In summary, our findings reveal a nuanced interplay of factors that influence crash severity on toll roads. Notably, male drivers were found to be more likely to be involved in crashes resulting in property damage, and young drivers, aged under 25 years, exhibited a heightened likelihood of property damage involvement but a reduced risk of severe injuries or minor or moderate injuries. Moreover, prior traffic rule violations, driver distraction, and specific crash characteristics like sideswipe collisions and surface conditions also played significant roles in determining crash outcomes. Roadway characteristics, such as posted speed limits and the presence of streetlights, further contributed to the complex landscape of crash severity. These insights underscore the multifaceted nature of road safety and offer valuable guidance for developing targeted interventions and policies to reduce the severity of road crashes. Among the variables considered, male drivers and drivers under 25 years old increased the likelihood of property damage. On the other hand, prior contributions, sideswipe collisions, and surface conditions reduced the likelihood of minor or minor injuries while posted speed limit greater than 60 mph and darkness increased the likelihood of minor or moderate injuries. Interestingly, in fatal or severe crashes, the likelihood decreased for variables such as driver distraction, prior movements, daylight conditions, posted speed limit less than 45 mph, and vehicle types classified as cars and SUVs.

The findings of this research have both intellectual merit and a broader impact to the improvement of safety on toll roads. The identified significant crash contributing factors can help in the planning and design of toll road infrastructure. The explored high-risk crash scenarios and common crash types can guide decisions about toll road layout, signage, lighting, and other safety features to make toll roads safer for all users. Findings from this research can inform the development of policies and regulations related to toll road safety. Advances in technology, such as intelligent transportation systems (ITS), can be informed by this research on toll road crashes. ITS can include features like real-time traffic monitoring, automated incident detection, and dynamic message signs to alert drivers about crashes and hazards.

In this study, the analysis emphasises that the RPLHM model is the most appropriate for characterising crash severities on toll roads. However, it is crucial to acknowledge the study's limitations. Unexplored factors, including road geometry elements (e.g. curvature, intersections), traffic conditions (e.g. density, presence of heavy vehicles), and driver behaviours (e.g. aggressive driving patterns, compliance with traffic rules), were not explicitly addressed. Moreover, other environmental conditions such as the presence of natural obstacles (trees, hills), infrastructure attributes like presence of guardrails or barriers, and emergency response times were omitted. It is noteworthy that with an expanded dataset incorporating more variables, there is the potential for a significant RPLHMV model, providing a more nuanced understanding of the factors influencing crash severities on toll roads. Additionally, an increased sample size would facilitate further analyses, such as exploring the temporal stability of parameters over time.

The study is not without limitation. It is important to note that RPLHM does face certain limitations, and the issue of cross-validation is acknowledged. However, it is pertinent to clarify that traditional cross-validation methods are not directly applicable to RPLHM due to its inherent complexity, especially when considering the incorporation of random parameters and heterogeneity in means. The unique nature of RPLHM makes the conventional cross-validation approach challenging to implement effectively.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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APPENDIX

Results for testing all parameters in the dataset to discover unobserved heteroscedasticity in means and variances. The following table (Table A1) presents the impact of each parameter in the data on the variance of random parameters. Each row signifies the effect of a specific variable on the variance of random parameters in an individual model.

Table A1. Heteroscedasticity in random parameters.

Variable	Coeff	t-stat	*p*-value
Vehicle light (1 if the headlights were off; 0 if were on)	0.170	0.69	0.491
Car (1 if the vehicle was a car; 0 otherwise)	0.220	0.94	0.345
SUV (1 if the vehicle was a SUV; 0 otherwise)	−0.462	−1.31	0.190
Young driver (1 if drivers age was less than 25; 0 otherwise)	−0.101	−0.39	0.698
Driver aged less than 25 years old (Young driver)	0.569	1.48	0.139
Distraction (0 if the driver was normal; 1 if driver was distracted)	−0.023	−0.10	0.920
Gender (0 if driver was female; 1 if driver was male)	0.106	0.29	0.772
Occupant's number (0 if single occupant; 1 otherwise)	0.447	0.80	0.423
Number of vehicles (0 if single vehicle; 1 otherwise)	−0.013	−0.04	0.970
Prior movement (0 if driver was moving straight; 0 1 if driver slowing to stop or stopped)	−0.463	−1.41	0.159
Movement reason (0 if driver was moving normal; 0 otherwise)	0.164	0.72	0.469
Rear end (1 if crash type was rear end; 0 otherwise)	−0.878	−1.19	0.236
Sideswipe (1 if it was a sideswipe collision; 0 otherwise)	0.191	0.58	0.565
Daylight (1 if crash happened during daylight; 0 otherwise)	0.300	0.86	0.389
Darkness (1 if the crash happened in darkness with no streetlight; 0 otherwise)	−0.763	−0.78	0.434
PSL [$<$ 45] (1 if the posted speed limit was less than 45 mph; 0 otherwise)	−0.350	−1.15	0.248
PSL [50–60] (1 if the posted speed limit was between 50 and 60 mph; 0 otherwise)	0.536	0.86	0.389
PSL [$>$ 60] (1 if the posted speed limit was greater than 60 mph; 0 otherwise)	0.208	0.73	0.467
Surface (1 if road surface was wet; 0 if it was dry)	−0.148	−0.47	0.638
Weather (1 if the weather was inclement; 0 if it was clear)	−0.304	−1.13	0.257

***, **, *: Significance at 1%, 5%, 10% level.