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Examining Driver Injury Severity in Single-Vehicle Road Departure Crashes Involving Large Trucks

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Abstract

Road departure (RD) crashes are among the most severe crashes that can result in fatal or serious injuries, especially when involving large trucks. Most previous studies neglected to incorporate both roadside and median hazards into large-truck RD crash severity analysis. The objective of this study was to identify the significant factors affecting driver injury severity in single-vehicle RD crashes involving large trucks. A random-parameters ordered probit (RPOP) model was developed using extensive crash data collected on roadways in the state of Kentucky between 2015 and 2019. The RPOP model results showed that the effect of local roadways, the natural logarithm of annual average daily traffic (AADT), the presence of median concrete barriers, cable barrier-involved collisions, and dry surfaces were found to be random across the crash observations. The results also showed that older drivers, ejected drivers, and drivers trapped in their truck were more likely to sustain severe single-vehicle RD crashes. Other variables increasing the probability of driver injury severity have included rural areas, dry road surfaces, higher speed limits, single-unit truck types, principal arterials, overturning-consequences, truck fire occurrence, segments with median concrete barriers, and roadside fixed object strikes. On the other hand, wearing seatbelt, local roads and minor collectors, higher AADT, and hitting median cable barriers were associated with lower injury severities. Potential safety countermeasures from the study findings include installing median cable barriers and flattening steep roadside embankments along those roadway stretches with high history of RD large-truck-related crashes.

Among others, road departure (RD) crashes could result in fatal or serious injury outcomes (*1*, *2*). (It is worth noting that the terms, RD and run-off-road [ROR] have been used interchangeably in previous studies to indicate crashes as a result of vehicles leaving the roadway.) RD crashes occur when an errant vehicle leaves its intended travel course to the left (median crossover) or to the right, resulting in striking one or more rigid fixed objects, overturning on roadside embankments, or colliding head-on with another vehicle in the opposite direction after crossing the median. Therefore, a sequence of off-roadway harmful events influences the level of severity to an errant vehicle (*2–5*). In the United States, RD crashes are responsible for over half of all traffic fatalities (*6*). In Portugal in Europe, single-vehicle RD crashes account for approximately half of freeway fatalities every year (*7*).

RD crashes even tend to be more serious when they involve large trucks (with gross vehicle weight rating > 10,000 lb). Because of its weight and dimension, an errant large truck leaving the roadway is highly likely to be involved in severe crash outcomes, following a collision with fixed hazards or overturning. According to the National Highway Traffic Safety Administration (NHTSA) in 2018, large-truck crashes accounted for about 4.4% of all reported crashes, while they were responsible for 9.4% of fatal crashes. Besides, collision with fixed objects made up 4.9% of the total fatalities involving large trucks in 2018 (*8*). These statistics necessitate an in-depth analysis of RD crashes involving large trucks.

Unforgiving roadside and median conditions, such as the presence of rigid fixed objects, steep embankments, and deep ditches, are highly associated with the severity of RD crashes (*7*, *9*). As a consequence, the safety of roadside and medians is considered an issue for transportation engineers and practitioners. However, the effects of roadside conditions on the severity of RD crashes have

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rarely been addressed in the literature. This might be a result of the lack of information on roadside features. This study aimed to fill that gap in the literature by examining the effects of various factors, including driver characteristics, roadway and traffic features, roadside and median conditions, and environmental characteristics, on driver injury severity in single-vehicle RD crashes involving large trucks. This study used a random-parameters ordered probit (RPOP) model using crash data collected on roadways in Kentucky between 2015 and 2019. The dependent variable was the crash severity level sustained by the driver in large-truck RD crashes. Because of very limited number of multi-vehicle RD crashes, this study focused on single-vehicle RD crashes involving large trucks, where the vehicle departed the roadway (from the median or roadside) and collided with a fixed object, or overturned, or finally rested.

Literature Review

Lee and Mannering (*10*) developed a nested logit model to evaluate the severity of ROR or RD crashes. The crash data were collected on State Route 3 in the state of Washington for the years 1994 to 1996. It was found that ROR crashes occurring in daytime, during peak periods, on weekend, during clear or cloudy weather conditions, on dry or wet road surfaces (compared with icy and snowy surface), on roadway sections with speed limits above 85 km/h, and on roadways with trees and guardrails were more likely to result in severe injury or fatality.

Spainhour and Mishra (*11*) used a logistic regression model to examine the relationship between various potential factors and overcorrection resulted from fatal ROR crashes. Data on crashes were collected on state-maintained roadways in Florida in 2000. The results showed that the presence of rumble strips, female drivers, paved or curbed shoulders, impaired driving, speeding, inattention, and fatigue or being asleep were the primary contributing factors affecting the likelihood of overcorrection, given that a fatal ROR crash had occurred. Using the same modeling approach, Peng and Boyle (*4*) examined the effects of various driver-related factors, such as speeding, fatigue, distraction, inattention, and seat belt use, on injurious and fatal ROR crashes involving trucks. Crash data were acquired from the Washington State Department of Transportation from 2006 to 2009. The authors found that not using seatbelt, driver distraction and inattention, drowsiness and fatigue, and speeding increased the likelihood of injurious and fatal ROR crashes. Apart from the aforementioned driver-related factors, rural roads and dry surfaces were also associated with severe ROR crashes. In another similar study, Zhu et al. (*12*) analyzed fatal ROR crashes along two-lane rural highways in the states of Alabama, Georgia, Mississippi, and South Carolina. The authors applied the binary logit models to estimate the probability that a fatal crash was a single-vehicle ROR fatal crash given roadway design features, environmental features, and traffic conditions at the crash location. A total of 557 crashes from the four states in 1997 and 1998 were used. They found that lane width, horizontal curvature, and presence of lighting were the three common significant factors affecting single-vehicle ROR crashes across all study locations.

Schneider et al. (*13*) investigated driver injury severity in single-vehicle crashes along horizontal curves on Texas rural two-lane highways. The multinomial logit models were adopted using a 5-year (1997–2001) crash data set. The results showed that striking a tree following ROR was the most significant factor associated with serious or fatal injuries. Other factors, including the combination of horizontal and vertical curvature, airbag deployment, driver age, female drivers, driver fatigue, impaired driving, and speeding, increased the likelihood of fatal crashes. In another study by Pardillo-Mayora et al. (*9*), a clustering analysis was used to develop a roadside hazardousness index (RHI) for Spanish two-lane rural roads based on the frequency and severity of ROR crashes. Data on traffic volumes and ROR injury crash records for a six-year period (2000–2005) were collected. The results showed that there was a high correlation between the calibrated RHI vales and ROR injury crashes.

Daniello and Gabler (*14*) used motorcycle crashes collected in the United States from 2004 to 2008 to compare the fatality risk of motorcycle collisions with the ground to that of collisions with roadside objects, including guardrails, concrete barriers, trees, signage, and utility poles. Their results showed that a collision with roadside barriers was at least 4 times more likely to be fatal than a collision with the ground. Among other objects, striking trees had the highest fatality risk, followed by collisions with signage and utility poles. Eustace et al. (*15*) adopted a generalized ordered logit model to identify the risk factors associated with the injury severity of ROR crashes that occurred between 2008 and 2012 in Ohio. The results showed that alcohol and drugs use, females, curves and grades, overturning crashes, and dry roadway surfaces increased the severity of ROR crashes.

Roque et al. (*7*) developed multinomial and mixed logit models to analyze the significant factors associated with driver severity and the most severely injured occupant in ROR crashes on Portuguese freeways. A total of 764 ROR crashes that occurred in 2009 and 2010 were used. The results showed that peak hours and straight segments reduced the driver injury severity likelihood in ROR crashes, whereas rollovers, higher speed limits, and roadside steep slopes increased the risk of major injury or fatality. In a similar study, Gong and Fan (*16*) applied a mixed logit model to examine the risk factors associated with driver injury severity in ROR crashes for different age groups, including young (ages 16–24), middle-aged (ages 25–65), and older drivers (ages over 65). Data on crashes were collected in North Carolina between 2009 and 2013. The modeling results showed that separate models for each age group were statistically favored over an all-age-group model. The results also showed that the effect of contributing factors differed across three age groups. Restraint use and horizontal curves were two significant factors affecting driver injury severity in all age groups, while driving violations, such as reckless driving or speeding were found to mainly affect the injury severity for young and middle-aged drivers rather than for older drivers.

Al-Bdairi and Hernandez (*17*) adopted an RPOP model to explore the impacts of truck, driver, environmental, and road characteristics on injury outcomes in ROR crashes involving large trucks. The crash data were collected from the state of Oregon for the years 2007 to 2013. The authors found that raised medians, loss of control of a vehicle, number of vehicles involved, month of crash occurrence, overtaking-related crashes, driver license status, use of safety equipment, alcohol consumption, driver fatigue, and the presence of horizontal curves were significantly associated with severe ROR crashes involving large trucks. Using the same database, Al-Bdairi et al. (*18*) examined the impact of lighting conditions on injury severity of ROR crashes involving large trucks. Two separate mixed logit models were developed for dark with no street lighting and lighted (daylight and dark with street lighting) conditions. The authors found that the effects of some factors, such as rural area, non-Oregonian drivers, and older drivers, varied between dark and lighted conditions.

Since RD crashes also involve median crossovers, this section summarizes studies that analyzed severity of median-related crashes. Donnell and Mason Jr (*19*) developed an ordered logit model to estimate the severity of median-related crashes on Pennsylvania interstate highways between 1994 and 1998. The results showed that weather condition, wet surface condition, crash type, impaired driving, and the presence of horizontal curve were associated with crash severity. In another study, Hu and Donnell (*20*) used binary logit and multinomial logit models to investigate the severity outcomes of cross-median and median rollover crashes, respectively. Information about crash data and roadway characteristics were gathered on rural divided highways in Pennsylvania during the years 2002 to 2006. The results showed that not wearing a seatbelt and narrower medians significantly affected the severity of cross-median and rollover crashes. In another study, Hu and Donnell (*21*) employed a nested logit model to examine the effects of roadway, environmental, and driver-related factors on median barrier crash severity on North Carolina interstate highways. Data on crashes were collected from the North Carolina Highway Safety Information System (HSIS) database for the years 2000–2004. Median barrier offset, travel speed, overturning, and curved road segment indicator were found to be associated with median barrier crash severity.

The literature review indicated that, with the exception of Al-Bdairi and Hernandez (*17*), Peng and Boyle (*4*), and Al-Bdairi et al. (*18*), there was no extensive research on RD crashes involving large trucks. Moreover, most previous studies devoted to RD crashes lacked analysis of the contribution of roadside and median-specific characteristics on the occurrence or injury severity outcomes in RD crashes. As a result, this study attempted to fill that gap by examining driver injury severity in large-truck single-vehicle RD crashes using comprehensive crash, roadway, roadside, median, driver, truck, and environmental characteristics collected from the state of Kentucky, as discussed next.

Data Collection and Processing

This study used five-year crash data collected on Kentucky roadways for the years 2015 to 2019. The information on crashes and road-specific characteristics were obtained from two different databases maintained by the Kentucky Transportation Cabinet (KYTC). The database related to roadway characteristics contained detailed information on road functional class, geometric design elements (such as lane width, median width, and right shoulder width), and traffic volume. Significant efforts were made by the research team to merge these two databases into a single database based on roadway identification number, the milepost of each crash, and the beginning and ending milepost of each segment. The final merged database included a comprehensive set of crash characteristics, driver demographics, truck conditions and configurations, geometric road design elements, roadside conditions, traffic volume and composition, and environmental features at the time of crash.

It should be noted that the crash database provided by KYTC did not include information on "the side of the road the vehicle ran off to." There was an indicator variable for "median crossover" in the original crash database. However, after careful review and investigation of several crash records by the research team, it was found that this indicator variable had many missing observations. Furthermore, this indicator variable did not provide reliable and accurate information on median RD or crossover crashes. In other words, it was quite impossible to distinguish between "median RD crashes from the left" and "ROR crashes from the right." Therefore, RD crashes were treated as a whole by investigating median-specific and roadside-specific characteristics on RD large-truck crashes (to improve the accuracy of the analysis and model results). Examples of median-specific characteristics were median barrier type, median width, and the first and second harmful events following large-truck single-vehicle RD crashes. Examples of roadside-specific characteristics were right shoulder width; type of right shoulder; and presence of embankments, bridges (including bridge rails, parapet ends), guardrails, traffic sign posts, utility poles, culverts, ditches, embankments, trees, and other fixed objects.

Because of the limited number of fatal RD crashes, using the KABCO scale, incapacitating (A) and fatal crashes (K) were combined to represent "severe injuries." Furthermore, non-incapacitating (B) and possible injuries (C) were combined to represent "minor injuries." After removing crash observations with missing values, 2,551 single-vehicle RD crashes involving large trucks were obtained. Of these, 2,053 (79%) RD crashes caused no injury (i.e., property damage only "PDO"), 425 (18%) involved minor injury, and 73 (3%) resulted in severe injury. Descriptive statistics of the data used are shown in Table 1.

Analytical Approach

Crash injury severity is generally regarded as an ordinal scale ranging from no injury (i.e., PDO) to fatality. To model such an ordinal variable, an ordered-response model, such as ordered probit or logit, is more appropriate. This approach is popular and widely used for the analysis of crash injury severities, where unordered choice models, for example, multinomial logit/probit model, do not account for the ordinal nature of the injury severities. Besides, these multinomial models are subject to undesirable properties, such as the lack of closed-form likelihood and the independence of irrelevant alternatives (IIA) (*22–24*). As a result, this study used an extension of the ordered probit (OP) model to analyze driver injury severity in large-truck single-vehicle RD crashes. In the data used, large-truck RD crash severities were scaled into three levels: no injury (PDO), minor injury (B + C), and severe injury (K + A). The response variable, driver injury severity, is ordered with the three levels. The observed injury level y is defined as follows:

$$y = \begin{cases} 0 \text{ if } & -\infty \leq y^* \leq 0 (\text{no injury}) \\ 1 \text{ if } & 0 < y^* \leq \mu_1 (\text{minor injury}) \\ 2 \text{ if } & \mu_1 < y^* \leq \infty (\text{severe injury}) \end{cases} \quad (1)$$

where μ_1 is an unknown threshold (cut-off) parameter to be estimated, and y^* is an unobserved (latent) variable that is estimated as:

$$y^* = \beta X + \varepsilon \quad (2)$$

where
X is a vector of independent variables,
β is the parameters to be estimated,
and ε is the random error term, which is assumed to be independent and identically-normal-distributed across the crashes.

A key constraint of the traditional OP model is that it fails to account for unobserved heterogeneity because of unmeasured characteristics. Failing to address the unobserved heterogeneity can lead to biased and inefficient parameter estimations (*18*, *25*). A random-parameters order probit (or RPOP) model can appropriately accommodate the effects of unobserved heterogeneity. The RPOP model allows the explanatory variables to vary across crash observations, as follows:

$$\beta_i = \beta + \varphi_i \quad (3)$$

where φ_i is a randomly distributed term capturing unobserved heterogeneity (for crash i).

In this study, random parameters are assumed to follow a normal distribution with mean 0 and variance σ^2, as the normal distribution has been reported to result in a better statistical fit in previous studies (*26–28*). An explanatory variable is considered to be random if the corresponding mean and standard deviation are statistically significant. As a consequence, the RPOP model is more flexible than the standard OP model, where the latter constrains the effects of all explanatory variables to be uniform across crash observations. To estimate the RPOP model, this study used a simulated maximum likelihood method based on 200 Halton draws, which have been reported to provide significantly more accurate results than purely random draws (*17*, *28–30*).

The "NLogit" statistical software package (*31*) was used to calibrate the RPOP model. To better interpret the impacts of significant variables on the probabilities of different severity levels, the marginal effects were estimated in this study. The marginal effects reflect the change in the probability of a specific injury severity outcome as a result of a one-unit increase in the value of a continuous variable or when an indicator variable changes from zero to one (*17*, *32*).

Goodness-of-Fit Assessment

The overall goodness-of-fit (GOF) measure for the RPOP model is determined by deviance statistic (D) and McFadden ρ^2 (*33*). These measures are calculated using Equations 4 and 5, as follows:

$$D = -2\ln\left(LL_0 - LL_\beta\right) \cong \chi^2_{(d.f.=p)} \quad (4)$$

Table 1. Descriptive Statistics of Explanatory Variables

Variable	Variable description	Mean	Standard deviation
Crash characteristics			
RD crash injury severity			
PDO	1 if true, otherwise 0	0.79	0.41
Minor injury	1 if true, otherwise 0	0.18	0.38
Severe injury	1 if true, otherwise 0	0.03	0.18
Roadway characteristics			
Road functional class			
Interstate	1 if true, otherwise 0	0.25	0.43
Principle arterial	1 if true, otherwise 0	0.10	0.30
Minor arterial	1 if true, otherwise 0	0.15	0.36
Major collector	1 if true, otherwise 0	0.20	0.40
Minor collector	1 if true, otherwise 0	0.12	0.33
Local	1 if true, otherwise 0	0.15	0.36
Unknown	1 if true, otherwise 0	0.03	0.16
IRI*	International Roughness Index (Min. = 21, Max. = 642)	102.04	56.5
Ln(AADT) *	Natural logarithm of annual average daily traffic (Min. = 3.97, Max. = 12.26)	8.72	1.70
HVP*	Heavy vehicle percentage (Min. = 0.0, Max. = 29.12)	12.92	11.28
Posted speed limit (mph)*	Min. = 25, Max. = 70	56.12	11.36
Area type			
Rural	If rural (population less than 5,000) = 1, otherwise = 0	0.69	0.46
Suburban	If suburban (population between 5,000 and 50,000) = 1, otherwise = 0	0.09	0.28
Urban	If urban (population greater than 50,000) = 1, otherwise = 0	0.20	0.40
Unknown	If area type not specified = 1, otherwise = 0	0.02	0.16
Type of road pavement	If concrete = 1, otherwise =0	0.06	0.24
Right shoulder width (ft)*	Min. = 0.0, Max. = 14.0	5.31	3.70
Type of right shoulder	If paved = 1, otherwise = 0	0.77	0.42
Work zone	If crash occurred at work zone = 1, otherwise = 0	0.02	0.14
Road alignment	If curved = 1, otherwise = 0	0.35	0.48
Vertical alignment	If upgrade or downgrade exists = 1, otherwise = 0	0.37	0.48
Two-lane indicator	If one lane per direction = 1, otherwise = 0	0.59	0.49
Lane width (ft)*	Min. = 6, Max. = 18	10.72	1.40
Undivided	If roadway is undivided = 1, otherwise = 0	0.51	0.50
Median width:			
No median	If no median = 1, otherwise = 0	0.51	0.50
Middle range	If median width between 4 and 39 ft. = 1, otherwise = 0	0.19	0.39
Wide	If equal or wider than 40 ft. = 1, otherwise = 0	0.14	0.35
Unknown	If median width unknown = 1, otherwise = 0	0.16	0.36
Median barrier type			
Cable	If true = 1, otherwise = 0	0.09	0.29
Concrete	If true = 1, otherwise = 0	0.10	0.31
Guardrail	If true = 1, otherwise = 0	0.01	0.03
No barrier	If true = 1, otherwise = 0	0.89	0.49
Climbing lane	If climbing lane is present = 1, otherwise = 0	0.01	0.09
Terrain type			
Flat	If true = 1, otherwise = 0	0.18	0.38
Rolling	If true = 1, otherwise = 0	0.61	0.49
Mountainous	If true = 1, otherwise = 0	0.05	0.22
Unknown	If true = 1, otherwise = 0	0.16	0.36
Crash location	If intersection = 1, otherwise = 0	0.15	0.35
First harmful event following RD			
Cable barrier	If 1st harmful event being colliding with cable barrier = 1, otherwise = 0	0.04	0.19
Tree	If colliding with tree = 1, otherwise = 0	0.05	0.21
Utility pole	If colliding with utility pole = 1, otherwise = 0	0.05	0.22
Traffic sign post	If colliding with traffic sign post = 1, otherwise = 0	0.02	0.15
Guardrail	If colliding with guardrail face or end = 1, otherwise = 0	0.12	0.32
Concrete/wall	If colliding with concrete barrier or wall = 1, otherwise = 0	0.04	0.19
Bridge	If colliding with bridge rail or bridge parapet end = 1, otherwise = 0	0.04	0.20

(continued)

Table 1. (continued)

Variable	Variable description	Mean	Standard deviation
Embankment ditch/cut/ culvert	If traversing or colliding with ditch/cut/culvert or embankment = 1, otherwise = 0	0.35	0.48
Fence	If colliding with fence = 1, otherwise = 0	0.02	0.13
Other small fixed object	If colliding with small fixed object (e.g., mailbox, curb, fire hydrant, etc.) = 1, otherwise = 0	0.12	0.33
No collision	If no 1st harmful crash event = 1, otherwise = 0	0.15	0.35
Second harmful event			
Tree	If 2nd harmful event being colliding with tree = 1, otherwise = 0	0.03	0.17
Utility pole	If colliding with utility pole = 1, otherwise = 0	0.02	0.14
Traffic sign post	If colliding with traffic sign post = 1, otherwise = 0	0.01	0.11
Guardrail	If colliding with guardrail face or end = 1, otherwise = 0	0.02	0.16
Concrete/wall	If colliding with concrete barrier or wall = 1, otherwise = 0	0.01	0.08
Embankment ditch/cut/culvert	If traversing or colliding with ditch/cut/culvert or embankment = 1, otherwise = 0	0.08	0.27
Overturning	If overturning = 1, otherwise = 0	0.21	0.41
Fence	If colliding with fence = 1, otherwise = 0	0.02	0.16
Other small fixed object	If colliding with small fixed object (e.g., mailbox, curb, etc.) = 1, otherwise = 0	0.03	0.17
No collision	If no 2nd harmful crash event = 1, otherwise = 0	0.02	0.13
Unknown	If second harmful event not specified = 1, otherwise = 0	0.55	0.50
Environmental characteristics			
Season of year			
Winter	If crash occurred in winter = 1, otherwise = 0	0.25	0.43
Spring	If crash occurred in spring = 1, otherwise = 0	0.25	0.43
Summer	If crash occurred in summer = 1, otherwise = 0	0.25	0.43
Autumn	If crash occurred in autumn = 1, otherwise = 0	0.25	0.44
Day of week	If crash occurred on weekend = 1, otherwise = 0	0.12	0.32
Weather condition			
Clear/cloudy	If clear or cloudy = 1, otherwise = 0	0.78	0.42
Foggy	If foggy = 1, otherwise = 0	0.01	0.11
Rainy	If rainy = 1, otherwise = 0	0.16	0.37
Snowy	If snowy = 1, otherwise = 0	0.05	0.21
Light condition			
Daylight	If true = 1, otherwise = 0	0.69	0.46
Dawn or dusk	If true = 1, otherwise = 0	0.05	0.21
Dark with light	If true = 1, otherwise = 0	0.06	0.24
Dark without light	If true = 1, otherwise = 0	0.20	0.40
Road surface condition			
Dry	If road surface was dry at time of crash = 1, otherwise = 0	0.71	0.45
Wet	If road surface was wet at time of crash = 1, otherwise = 0	0.23	0.42
Icy	If road surface was icy at time of crash = 1, otherwise = 0	0.06	0.24
Driver characteristics			
Driver gender	If male = 1, otherwise = 0	0.96	0.19
Driver age			
Young	If driver's age under 30 years = 1, otherwise = 0	0.18	0.39
Middle	If driver's age between 31 and 59 years = 1, otherwise = 0	0.67	0.47
Old	If driver's age 60 years or above = 1, otherwise = 0	0.14	0.35
Unknown	If driver's age unknown = 1, otherwise = 0	0.01	0.08
Driver residence status	If Kentucky resident = 1, otherwise = 0	0.16	0.36
Seatbelt	If seatbelt used = 1, otherwise = 0	0.96	0.21
Driver behavior			
Drowsiness	If true = 1, otherwise = 0	0.03	0.18
Alcohol	If true = 1, otherwise = 0	0.01	0.09
Drug	If true = 1, otherwise = 0	0.01	0.07
Aggressiveness	If true = 1, otherwise = 0	0.01	0.11
Distraction	If true = 1, otherwise = 0	0.24	0.43
Speeding	If true = 1, otherwise = 0	0.03	0.17
No dangerous behavior	If true = 1, otherwise = 0	0.67	0.46

(continued)

Table 1. (continued)

Variable	Variable description	Mean	Standard deviation
Driver action before crash			
Going straight ahead	If true = 1, otherwise = 0	0.06	0.24
Avoiding object on road	If true = 1, otherwise = 0	0.92	0.27
Other maneuver	If true = 1, otherwise = 0	0.02	0.13
Driver trapped	If driver was trapped in the vehicle = 1, otherwise = 0	0.05	0.21
Driver ejected	If driver was ejected out of the vehicle = 1, otherwise = 0	0.01	0.08
Truck characteristics			
Truck class			
Single-unit truck	If true = 1, otherwise = 0	0.29	0.45
Tractor and semi-trailer	If true = 1, otherwise = 0	0.56	0.50
Tractor and trailer	If true = 1, otherwise = 0	0.13	0.33
Other combination	If true = 1, otherwise = 0	0.02	0.16
Airbag deployment status			
Not deployed	If airbag not installed or deployed = 1, otherwise = 0	0.98	0.14
Deployed-front	If front airbag deployed = 1, otherwise = 0	0.01	0.10
Deployed-unknown	If airbag deployment unknown = 1, otherwise = 0	0.01	0.08
Fire occurrence	If there was fire involved = 1, otherwise = 0	0.01	0.09

Note: Min. = minimum; Max. = maximum; PDO = property damage only; RD = road departure.
*Continuous (non-discrete) variable.

$$\rho^2 = 1 - \left({}^{LL_\beta}\!/_{LL_0}\right) \tag{5}$$

where
LL_β is the log-likelihood at convergence,
LL_0 is the log-likelihood of the null model (i.e., constant-only model), and
p is the number of predictors in the final model.
A significant value for the deviance statistic indicates a good statistical fit.

RPOP Model Results and Discussion

This section presents the results of the RPOP model developed to identify the risk factors affecting driver injury severity in large-truck single-vehicle RD crashes. Table 2 shows the results of the RPOP model. (To gain a better insight into the combined impact of first and second harmful events on RD crash severity, this study considered the interaction effects of different events along with their main effects in the modeling process.) However, because of excessive inflation of the standard errors of the coefficients, the interaction terms were not found significant in the final model). The model GOF measures, including the deviance statistic (665.12, P-value < 0.01) and McFadden ρ^2 value (0.23) indicate a reasonable overall fit of the RPOP model. Twenty-four variables were found to significantly affect driver injury severities in large-truck single-vehicle RD crashes. Of those, five variables were found to be random (under the normal distribution). These were local roadway, natural logarithm of AADT "Ln(AADT)," the presence of median concrete barriers, cable barrier-involved collisions, and dry surfaces. This indicates that the effects of these variables were not fixed across the crash observations. For example, local roadways had a random effect with a mean of -0.675 and standard deviation of 0.635. This means that local roadways reduced the probability of driver injury severity for 86% of single-vehicle RD crashes and increased the probability for 14% of the observations. For the remaining variables in the model, the corresponding standard deviations were not statistically different from zero; therefore, their effects were fixed.

Roadway Characteristics

On road functional class, single-vehicle RD crashes occurring on local and minor collectors were associated with less severe injury outcomes, while those occurring on principal arterials increased the likelihood of severe injuries. This result might be a result of local and minor collectors representing road sections with lower speed limits, where drivers tend to drive more slowly and cautiously when traveling on such roadways, thereby reducing the likelihood of a severe injury. By contrast, because of higher speed limits and more traffic lanes on principal arterials (e.g., interstates and expressways), large-truck drivers are likely to travel more aggressively, which increases the risk of severe injuries when a single-vehicle RD crash occurs. This result was also found by past research (*34*).

Ln(AADT) was another significant factor with a varying effect (mean of -0.070 and standard deviation

Table 2. RPOP Model Estimates of Driver Severity in Large Truck Single-Vehicle RD Crashes

Variable	Coefficient	Standard error	Z-Stat.	P-Value	Marginal Effects (%)*		
					No Injury	Minor Injury	Severe Injury
Constant	−0.586	0.340	−1.72	0.085			
Roadway characteristics							
Road functional class							
Principle arterial	0.192	0.112	1.71	0.087	−3.34	3.32	0.03
Minor collector	−0.245	0.123	−2.00	0.046	3.39	−3.37	−0.02
Local**	*−0.675*	*0.142*	*−4.74*	*0.001*	7.70	−7.65	−0.05
SD of parameter distribution	*0.635*	*0.123*	*5.15*	*0.001*	na	na	na
Ln(AADT)**	*−0.070*	*0.034*	*−2.04*	*0.042*	1.20	−1.09	0.09
SD of parameter distribution	*0.081*	*0.005*	*17.34*	*0.001*	na	na	na
Posted speed limit (mph)	0.010	0.005	2.12	0.034	−0.15	0.15	0.01
Area type: Rural	0.174	0.104	1.67	0.094	−2.62	2.60	0.02
Median barrier type: Concrete**	*0.305*	*0.140*	*2.18*	*0.029*	−5.62	5.56	0.06
SD of parameter distribution	*0.549*	*0.105*	*5.21*	*0.001*	na	na	na
First harmful event:							
Cable barrier**	*−0.959*	*0.386*	*−2.49*	*0.013*	8.08	−8.04	−0.04
SD of parameter distribution	*1.190*	*0.323*	*3.69*	*0.001*	na	na	na
Traffic sign post	−0.693	0.336	−2.06	0.039	6.83	−6.79	−0.04
Small fixed objects	−0.696	0.173	−4.01	0.001	7.65	−7.60	−0.05
Second harmful event							
Tree	0.954	0.176	5.41	0.001	−24.88	24.20	0.678
Utility pole	0.656	0.230	2.85	0.004	−15.12	14.84	0.28
Guardrail	0.699	0.203	3.45	0.001	−16.40	16.08	0.32
Concrete/wall	0.713	0.383	1.86	0.063	−17.03	16.69	0.34
Embankment ditch/cut/culvert	0.433	0.127	3.40	0.001	−8.60	8.49	0.11
Overturning	0.730	0.085	8.57	0.001	−15.05	14.81	0.23
Environmental and driver characteristics							
Dry road surface**	*0.168*	*0.082*	*2.07*	*0.039*	−2.53	2.51	0.02
SD of parameter distribution	*0.468*	*0.043*	*10.77*	*0.001*	na	na	na
Seatbelt used	−1.298	0.132	−9.85	0.001	37.31	−35.71	−1.60
Older driver (⩾ 60 years)	0.172	0.096	1.79	0.073	−2.95	2.92	0.03
Driver trapped	2.189	0.143	15.26	0.001	−69.35	59.56	9.79
Driver ejected	2.132	0.363	5.87	0.001	−69.06	58.69	10.37
Truck characteristics							
Truck class: single-unit truck	0.296	0.079	3.77	0.001	−5.08	5.03	0.05
Airbag status: deployed-front	0.861	0.284	3.03	0.002	−21.93	21.39	0.54
Fire occurrence	1.432	0.322	4.45	0.001	−43.79	41.31	2.48
Threshold μ_1	2.014	0.102	19.81	0.001	na	na	na
Goodness-of-fit (GOF) statistics							
Number of observations				2,551			
Number of parameters				31			
Log-likelihood at zero (LL_0)				−1466.97			
Log-likelihood at convergence (LL_β)				−1134.41			
DevianceStatistic (P-Value)				665.12 (< *0.01*)			
McFadden ρ^2				0.23			

Note: SD = standard deviation; RPOP = random-parameters ordered probit; AADT = annual average daily traffic; na = not applicable.
*Denotes % change in each category.
**Randomly-distributed parameter.

of 0.081) on driver injury severity of large-truck single-vehicle RD crashes. This means that for about 81% of the crash observations, AADT reduced the injury severity, while for the rest, that effect was the reverse. This result is mainly because of the lower travel speeds associated with high vehicular traffic on the roadway, which diminish the risk of severe crashes (*35*). This finding was supported by the higher severity risk with higher speed limits. This might be since high speed limits are mainly posted on rural roadways or multilane road segments, where the likelihood of speeding and other risky driving maneuvers is high. This result is consistent with those of previous studies (*24*, *36–38*).

In accordance with the previous "posted speed limit" finding, large-truck single-vehicle RD crashes occurring on rural roadways were more severe. This finding may be

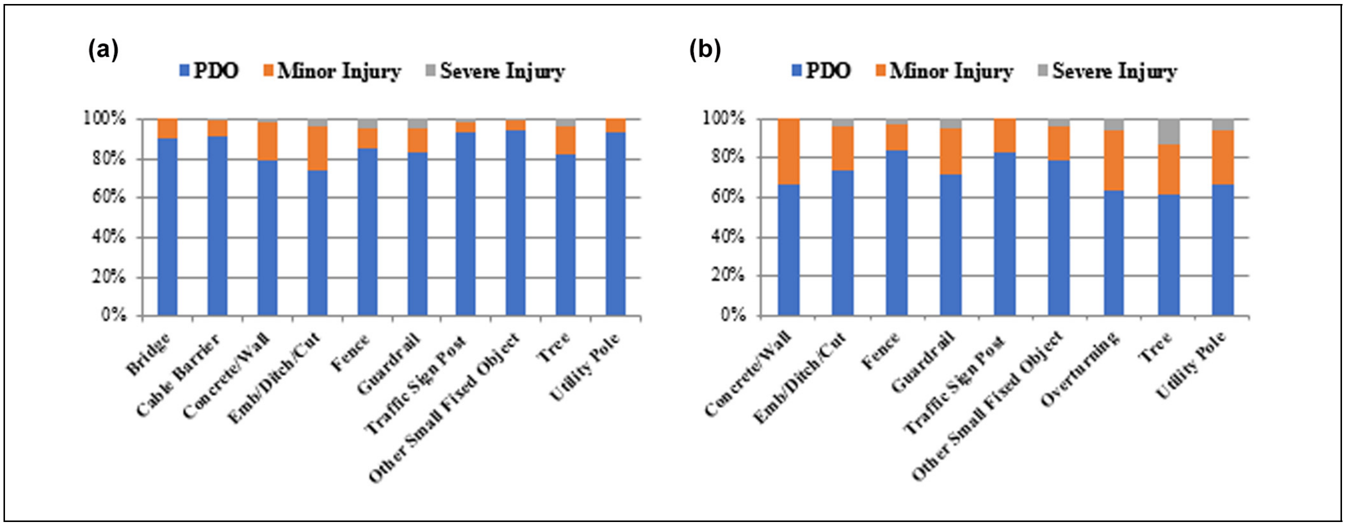

Figure 1. Percentage distribution of RD crash injury severity levels for: (*a*) first harmful events, and (*b*) second harmful events.
Note: RD = road departure; PDO = property damage only.

rationalized by rural roadways representing higher speed limits and lower traffic volumes (*1*, *7*, *39*).

In median-related characteristics, large-truck driver injury was more severe for roadway segments with concrete barriers installed on the median (random parameter with mean of 0.305 and standard deviation of 0.549). The presence of median concrete barriers was found to increase the risk of minor injuries by 5.56%. Although concrete barriers prevent errant vehicles from being involved in RD-related crashes, they may increase the likelihood of serious injuries when a large truck runs off the roadway and hits such rigid structures (*40*).

An interesting and rarely explored finding from this study is about the harmful events in large-truck single-vehicle RD crashes. The results showed that overturning and collision with roadside hazardous objects including trees, guardrails, concrete barriers or walls, utility poles, and embankment/ditches/cut/culvert were found to significantly increase the risk of driver severe injuries, whereas hitting median cable barriers (random parameter with mean of −0.959 and standard deviation of 1.190), traffic sign posts, and small fixed objects (such as mailbox and curb) lessened the sever injury probability. These results are reasonable, as overturning or colliding with rigid objects, especially trees, potentially lead to higher injury severities when the truck departs the roadway. On the other hand, median cable barriers, traffic sign posts, and small fixed objects (e.g., mailbox) are flexible, fragile objects. Therefore, crashing into such non-rigid objects is less likely to result in severe injuries. Such findings can be supported by previous studies (*2*, *7*, *18*, *35*, *41–43*).

To further assess the impact of first and second harmful events, Figure 1, *a* and *b*, show the percentage distribution of single-vehicle RD crash injury severity levels for the first and second harmful events, respectively, following a large-truck RD crash. As shown, the second harmful events, especially overturning and colliding with trees or utility poles, were more responsible for driver injury severity when compared with the first harmful events.

Environmental and Driver Characteristics

The only significant factor related to environmental conditions was dry surface condition (random parameter with mean of 0.168 and standard deviation of 0.468). Because of the randomness effect, this variable was found to increase the driver injury severity for 64% of large-truck single-vehicle RD crashes. This result might be because drivers tend to travel aggressively in dry surface conditions. A similar finding was reached by past studies (*10*, *15*, *36*, *40*, *44*).

The "seatbelt use" indicator variable was significantly associated with lower driver injury severity in large-truck single-vehicle RD crashes. This result is rational, as wearing a seatbelt significantly reduces the risk of injury when a severe crash occurs. From the marginal effect, wearing a seatbelt reduced the risk of minor and severe RD-related injuries by 35.71% and 1.6%, respectively. Older drivers (at or above 60 years of age) were associated with increased probability of severe injury following a large-truck single-vehicle RD crash. This result might be because older drivers have longer reaction times and poor physical conditions (compared with their younger and middle-age counterparts). Therefore, they are more likely to sustain serious injuries (*16*, *24*, *35*, *45*, *46*).

To further assess the impact of large-truck driver age, Figure 2 presents the percentages of total and severe RD

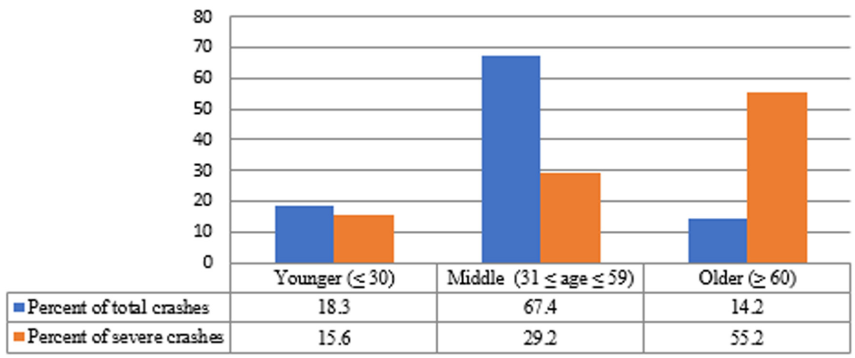

Figure 2. Percentages of total and severe road departure (RD) injury crashes among different driver age groups.

injury crashes among different age groups. As seen, older drivers accounted for about 55% of severe crashes (the highest percentage), while they only made up 14% of total crashes. Middle-aged drivers were responsible for 29% of severe crashes, yet comprised over two-thirds of total crashes. Younger drivers had the least proportions for both total and severe crashes. This shows that older large-truck drivers were the most prone age group to sustain severe single-vehicle RD crashes.

Drivers being trapped in the truck were found to experience more severe injuries when a large-truck single-vehicle RD crash had occurred. This result is intuitive, as being trapped in vehicles contributes to more serious outcomes (*47*, *48*). Similarly, drivers ejected from the truck were associated with severe injuries in large-truck single-vehicle RD crashes (*49*, *50*). This finding emphasizes the importance of wearing a seatbelt to avoid ejection from the large-truck. According to the marginal effects, being trapped or ejected from the truck increased the probability of severe injury by approximately 10% on average.

Truck Characteristics

Single-vehicle RD crashes involving single-unit trucks were found to increase the probability of driver injury severity. This result could be partially explained by single-unit trucks having smaller size and lower weight compared with other large-truck classes (e.g., tractors and trailers). Therefore, drivers operating single-unit trucks are more likely to drive aggressively. Frontal airbag deployment was another vehicle-related factor associated with higher driver injury severity in truck-involved single-vehicle RD crashes. A possible explanation is that airbags are deployed when a severe speed-related crash takes place. Therefore, drivers are more prone to being severely injured. This finding is in line with those of previous studies (*32*, *37*). Finally, large-truck single-vehicle RD crashes resulting in fire occurrence led to more severe injuries, which is an expected consequence. Previous studies reported similar findings (*24*, *51*). Based on the marginal effects, a fired large truck after the RD crash was found to increase the probabilities of minor and severe RD-related injuries by 41.31% and 2.48%, respectively.

Conclusions and Practical Implications

This study examined the effects of different factors on driver injury severity in single-vehicle RD crashes involving large trucks. To the authors' best knowledge, few studies have incorporated roadside- and median-related attributes in RD crash analysis. Besides, research on large-truck RD crashes is still limited in the current literature. Therefore, this study extends the current research by investigating driver injury severity in large-truck single-vehicle RD crashes. Comprehensive crash, roadway, roadside, median, driver, truck, and environmental characteristics were explored. An RPOP model was developed using five-years of data on crashes collected on roadways in the state of Kentucky from 2015 to 2019.

The RPOP modeling results showed that older drivers, ejected drivers, and operators trapped in their truck were more likely to get involved in severe single-vehicle RD crashes. Other variables increasing the probability of driver injury severity have included rural areas, dry road surfaces, higher speed limits, front airbag deployment, single-unit trucks, principal arterials, overturning-consequences, truck fire occurrence, and segments with median concrete barriers. On the other hand, wearing a seatbelt, local roads and minor collectors, and higher AADT were associated with lower injury severities.

The second harmful events increasing the risk of driver injury severity have included overturning and hitting roadside rigid objects, such as trees, utility poles, embankments/ditches/cut/culvert, guardrails, and concrete barriers/walls. The first harmful events found to reduce the risk of severe large-truck single-vehicle RD crashes were collisions with median cable barriers, traffic sign posts, and fragile small objects (e.g., mailboxes and curbs).

The results of this study can be used by transportation agencies and road safety researchers to gain greater insights into the real impacts of various factors associated with the severity of large-truck single-vehicle RD crashes. For road safety barriers, this study found that median cable barriers resulted in lesser severe injuries. As a result, the installation of median cable barriers could be an effective countermeasure to reduce the severity of single-vehicle large-truck RD-related collisions.

This research was strengthened by examining the individual effects of each of the first and second harmful events (and not necessarily the most harmful event). The results showed that roadside hazards, such as embankments, ditches/cuts, trees, and utility poles, significantly increased driver injury severity in large-truck single-vehicle RD crashes. Effective countermeasures targeting such unforgiving environments could include flattening steep embankments, shielding unremovable fixed objects (e.g., trees) through installing safety barriers along roadway stretches with high history of RD truck-related crashes (*1*, *52–55*), and installing shoulder rumble strips. For example, Hildebrand et al. (*56*) reported that widening roadside clear zones (beyond the right shoulder) from less than 6 m (19.7 ft) to between 6 m (19.7 ft) and 10 m (32.8 ft) reduced RD collision rates by 40%. Another case study on Illinois freeways indicated that installing shoulder rumble strips reduced single-vehicle RD crashes by about 21% (*57*).

In this regard, future cost–benefit analysis could quantify the safety benefits of different countermeasures in mitigating the occurrence and severity outcomes of RD crashes. Another future study is to examine the effects on injury severity of more detailed roadside attributes, such as the type and number of roadside hazards and their offset from the roadway edge. This could help gain useful insights into the real effects of various roadside conditions on large-truck driver injury severity.

To generalize and extend the main conclusions obtained in this study, the use of a larger data set from other states, where roadway geometric design, environmental conditions, and traffic characteristics may differ from those studied in this research in Kentucky is recommended. This may help assess how the findings of this study would be transferable to other locations.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Kirolos Haleem and Mehdi Hosseinpour; data collection: Mehdi Hosseinpour; analysis and interpretation of results: Mehdi Hosseinpour; draft manuscript preparation: Mehdi Hosseinpour and Kirolos Haleem. All authors reviewed the results and approved the final manuscript version.

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