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Factors influencing injury severity of crashes involving HAZMAT trucks

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ABSTRACT

This paper investigates factors affecting injury severity of crashes involving HAZMAT large trucks. It uses the crash data in the state of California from the Highway Safety Information System, from 2005 to 2011. The explanatory factors include the occupant, crash, vehicle, roadway, environmental, and temporal characteristics. Both fixed- and random-parameters ordered probit models of injury severity (where possible outcomes are *major*, *minor*, and *no injury*) were estimated; the random-parameters model captures possible unobserved effects related to factors not present in the data. The model results indicate that the occupants being male, truck drivers, crashes occurring in rural locations, under dark-unlighted, under dark-lighted conditions, and on weekdays were associated with increased probability of major injuries. Conversely, the older occupants (age 60 and over), truck making a turn, rear-end collision, collision with an object, crashes occurring on non-interstate highway, higher speed limit highway (≥65 mph), and flat terrain were associated with decreased probability of major injuries. This study has identified factors that explain injury severities of crashes involving HAZMAT, and as such, it could be used by policy makers and transportation agencies to improve HAZMAT transport, and thus, the overall highway safety.

Introduction

The transport of hazardous materials (HAZMAT) is complex and poses serious safety, security, and environmental concerns. HAZMATs are capable of producing catastrophic effects on public health, public safety, environment, and property, if released. The transport of HAZMAT ranges from a single shipment of gasoline in a container moved by a truck to bulk shipments of poisonous, explosive, or radioactive materials in tanks moved by vessels (Transportation Research Board, 2009). According to the Commodity Flow Survey, in 2012, approximately 2.6 billion tons of HAZMAT was moved on the U.S. transportation network by all the modes. Trucks moved about 60% of these HAZMATs by tonnage (U.S. Census Bureau, 2015).

HAZMAT crashes on highways often result in more severe injuries, although the number of crashes is low relative to the amount of HAZMAT that moves on the highway. In 2014, a total of 3744 large trucks were involved in fatal crashes in the U.S., of which 112 (about 3%) were carrying HAZMAT (FMCSA, 2016). A single crash involving a HAZMAT vehicle in a densely-populated area has a much greater potential to cause significant casualty, injury, and damage to the environment and

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property than that of a typical commercial vehicle. Indeed, the majority of HAZMAT crashes lead to extensive property damage and network disruption (Craft, 2004). Furthermore, HAZMAT crashes can increase the injury risk due to fires immediately after the crash; this might occur if vehicle carries gasoline or diesel. The incidents involving truck transport of HAZMAT have adverse economic impact. For instance, the total cost of Class 3 (flammable and combustible liquid) HAZMAT incidents was about $459 million in 1996 (Abkowitz et al., 2001). The severity of these type of crashes highlights the need to investigate factors that contribute to HAZMAT truck crashes.

There have been a number of studies investigating the risk factors that contribute to injury severity of truck-involved crashes. Duncan et al. (1998) developed an ordered probit model to determine the significant variables that influence levels of injury when truck and passenger cars are involved in rear-end collisions on divided roadways. The authors used the 1993–1995 North Carolina crash data from the Highway Safety Information System (HSIS). Chang and Mannering (1999) developed nested logit models to study the injury severity of occupants for both truck-involved and non-truck-involved crashes using the 1994 crash data from King County in Washington. Their study found that crashes involving trucks had higher injury severity than those that do not involve trucks. Khorashadi et al. (2005) studied the difference between rural and urban driver injury severities in truck-involved crashes. The authors used multinomial logit models to analyze the 1997–2000 California crash data. Zhu and Srinivasan (2011) explored crash, vehicle, and driver factors that influence injury severity of truck-involved crashes. They used ordered probit model to analyze crashes that occurred between April 2001 and December 2003 from the Large Truck Crash Causation Study (LTCCS). Lemp et al. (2011) used both standard and heteroskedastic ordered probit models to identify the factors influencing injury severity of truck-involved crashes. The authors used the LTCCS crash data from 17 states to determine the crash factors. Islam and Hernandez (2013a) analyzed truck-involved crash factors using random-parameters ordered probit model and the 2005–2008 National Automotive Sampling System General Estimates System data. They analyzed human, vehicular, road, environmental, and crash factors that influence injury severity of truck-involved crashes. In another study, Islam and Hernandez (2013b) developed mixed logit models using the 2006–2010 Texas Peace Officer's Crash Reports database. Islam et al. (2014) developed four mixed logit models to analyze single- and multi-vehicle truck-involved crashes on both rural and urban roadways in Alabama. All four of their models focused exclusively on crashes where trucks were at fault. Cerwick et al. (2014) compared the performance of mixed logit models and latent class methods in modeling truck-involved crash injury severity using the 2007–2012 Iowa crash data. Pahukula et al. (2015) studied the effect of time of day on injury severity of truck-involved crashes. They used the 2006–2010 Texas Peace Officer's Crash Reports database and mixed logit models to identify significant factors. Most recently, Uddin and Huynh (2017) investigated factors affecting injury severity of crashes involving trucks for different lighting conditions on rural and urban roadways using the 2009–2013 Ohio crash data from the HSIS database. In summary, none of the aforementioned studies have considered HAZMAT as one of the crash factors in analyzing injury severity of truck-involved crashes.

The current body of literature on crash injury severity factors in road transport of HAZMAT is limited. Khattak et al. (2003) studied the risk factors associated with large-truck rollovers and injury severity of occupants in single-vehicle crashes in North Carolina from 1996 to 1998. The authors concluded that occupants of truck carrying HAZMAT received more severe injuries. The chance of injuries for trucks carrying HAZMAT was found to increase by about 16%. Oggero et al. (2006) studied 1932 HAZMAT crashes and found that the majority of the crashes were releases, followed by fires, explosions and gas clouds. Carson (2007) studied 44,012 large-truck crashes in Texas from 2004 to 2006 and found that HAZMAT interstate carriers were involved in about 2% of the total crashes. Chen and Chen (2011) analyzed single- and multi-vehicle crashes involving trucks on rural highways in Illinois from 1991 to 2000. For cases involving single-vehicle crashes, about 22% of the truck drivers suffered incapacitating or fatal injury when the truck was carrying HAZMAT. For cases involving multi-vehicle crashes, about 11% of the truck drivers suffered incapacitating or fatal injury. The study concluded that the probability of incapacitating or fatal injury experienced by truck drivers would increase significantly if the truck carries HAZMAT; specifically, about 48% for single-vehicle crashes and about 49% for multi-vehicle crashes. Shen et al. (2014) analyzed 708 road tank truck crashes associated with HAZMAT in China from 2004 to 2011. They found that about 56% of the HAZMAT crashes occurred on freeways and these crashes had a high percentage of HAZMAT spills. Rollover, run-off and rear-end collision crashes had the higher likelihood of large spills. The majority of the crashes occurred in July and during the early morning hours (4 am–6 am) and mid-day hours (10 am–12 pm). The study concluded that human errors and vehicle defects were the main reasons behind those HAZMAT crashes. All of the aforementioned studies have explored the effect of HAZMAT on injury severity of truck-involved crashes via the use of an explanatory variable. This approach is simplistic, and thus, provides limited information about the relationship between HAZMAT and injury severity. Given that HAZMAT-related crashes have different characteristics than that of typical truck-involved crashes such as having higher injury risk and occurring on HAZMAT designated routes, a disaggregate approach is needed to better understand the contributing crash factors to this type of crashes.

The purpose of this current study is to investigate factors that contribute to HAZMAT crashes on highways, where at least one of the vehicles involved is a HAZMAT large truck, using discrete choice models; particularly, the ordered probit model. The analysis is done by combing three separate datasets (crash, vehicle, and occupant) from the Highway Safety Information System (HSIS) database into one master dataset that has all the explanatory variables, including occupant, crash, vehicle, roadway, environmental, and temporal factors. In addition to using the standard ordered models to identify the significant contributing factors on injury severity, a random-parameters ordered probit model is developed to account for unobserved heterogeneity in the data. Lastly, average direct pseudo-elasticities are calculated to determine the net change in the effect of significant variables on the different injury severity levels.

Methodology

There have been numerous studies that examined the relationship between crash factors and injury severity levels using discrete choice models, such as ordered probit/logit models, nested logit models, and multinomial logit models (cf. Savolainen et al., 2011). Several of these studies have utilized ordered models since the dependent variable (e.g., injury severity) is ordered in nature (e.g., no injury, minor injury, and major injury) (Abdel-Aty, 2003; Duncan et al., 1998; Obeng, 2011; Pai and Saleh, 2008; Quddus et al., 2002; Zhu and Srinivasan, 2011). Furthermore, compared to other discrete choice models, the differences between the ordinal categories are not assumed to be equal in ordered models (McKelvey and Zavoina, 1975). For these reasons, an ordered probit model is used to determine the factors that affect injury severity in HAZ-MAT truck crashes. To account for factors that can vary across observations, this study adopts the random-parameters probit model in addition to the standard fixed-parameters model. Examples of the fixed-parameters ordered probit model for analyzing injury severity can be found in the works by Abdel-Aty (2003) and Obeng (2011), and those of random-parameters ordered probit model can be found in the work by Islam and Hernandez (2013a).

Following the methodology presented in Washington et al. (2011), let the variable y^* be defined as a latent and continuous measure of injury severity for each observation n.

$$y^* = \boldsymbol{\beta X} + \varepsilon \tag{1}$$

where y^* = dependent variable; $\boldsymbol{\beta}$ = vector of coefficients to be estimated; $\boldsymbol{X}$ = vector of explanatory variables (e.g., occupant, crash, vehicle, roadway, environmental, and temporal factors); and ε = random error term (assumed to be normally distributed across observations with mean 0 and variance 1).

Under the ordered probit framework and Eq. (1), the observed ordinal data y (i.e., injury severity) for each observation are defined as follows (Washington et al., 2011).

$$\begin{aligned} &y = 1 \quad \text{if } y^* \leqslant \mu_0 \\ &y = 2 \quad \text{if } \mu_0 \leqslant y^* \leqslant \mu_1 \\ &\ldots \\ &y = I \quad \text{if } y^* \geqslant \mu_{I-1} \end{aligned} \tag{2}$$

where μ is threshold between two adjacent injury levels that define y and is estimated jointly with the model coefficients $\boldsymbol{\beta}$; and I is the highest integer order injury severity level. The ordered selection probabilities can be calculated as follows (Washington et al., 2011).

$$\begin{aligned} &P_n(y = 1) = \Phi(-\boldsymbol{\beta X}) \\ &P_n(y = 2) = \Phi(\mu_1 - \boldsymbol{\beta X}) - \Phi(-\boldsymbol{\beta X}) \\ &\ldots \\ &P_n(y = I) = 1 - \Phi(\mu_{I-1} - \boldsymbol{\beta X}) \end{aligned} \tag{3}$$

where $P_n(y = I)$ is the probability that y is the highest ordered injury severity level at observation n, given a crash occurred; and $\Phi(\cdot)$ = cumulative normal distribution.

With the consideration of random parameters, it is possible to minimize inconsistent, inefficient, and biased parameter estimates (Washington et al., 2011). As such, the random-parameters ordered probit model is formulated by considering an error term, which is correlated with the unobserved factors in ε. The observation heterogeneity is then translated into parameter heterogeneity as follows (Greene, 2003).

$$\beta_n = \beta + \gamma_n \tag{4}$$

where γ_n = randomly distributed term (e.g., a normally distributed term with mean 0 and variance σ^2).

The random parameters of the ordered probit model can be estimated using the *simulated* maximum likelihood method and using Halton draws to maximize the simulated log-likelihood function (Christoforou et al., 2010). The functional form of the parameter density function can be either normal, lognormal, triangular, or uniform (Anastasopoulos and Mannering, 2009; Gkritza and Mannering, 2008; Islam and Hernandez, 2013a).

The estimated parameters from the ordered models are not sufficient to determine the direction and magnitude of the effect of the intermediate crash severity levels. For that reason, elasticity values of the parameters are often used for the interpretation of the effect of the parameters on the probability of the injury severity levels. When the explanatory variables are binary indicator variables (with value 0 or 1), direct pseudo-elasticity are used for each severity level and each observation. The direct pseudo-elasticity for the explanatory variables is computed as follows (Kim et al., 2008).

$$E_{X_{ink}}^{P_{in}} = \frac{P_{in}[\text{given } X_{ink} = 1] - P_{in}[\text{given } X_{ink} = 0]}{P_{in}[\text{given } X_{ink} = 0]} \tag{5}$$

where P_{in} is defined by Eq. (3) and X_{ink} is the k-th explanatory variable associated with severity level i for the crash observation n. Then, the average direct pseudo-elasticity is calculated for each injury severity level (Kim et al., 2008).

Data and empirical setting

The data used in this study consist of seven years of crash records (2005–2011) involving HAZMAT trucks in the state of California, provided by the Highway Safety Information System (HSIS). HSIS provides highway patrol reported data about crashes, and information about occupants, vehicles, and roadways involved in the crash.

The severity of crashes is recorded as one of five injury levels in the HSIS dataset. They are commonly defined using the KABCO injury scale: fatality (K), disabling injury (A), evident injury (B), possible injury (C), and no injury (O). The fatal injury includes crashes which result in death of occupant(s) within 30 days of crash. The disabling injury prevents the injured person from walking, driving, or normal activities the person was capable of performing before the injury. The evident injury includes crashes where injury is evident to observers at the crash location. The possible injury is one where the occupant complains of pain, but it diminishes rapidly from the time of evaluation at the crash location to the time of examination at the hospital. Lastly, the no injury is where the reported crash does not result in any injury. The KABCO injury codes presented in the dataset were consolidated into three levels—major injury (KA), minor injury (BC), and no injury (O)—to ensure that a sufficient number of observations is available in each injury severity level. Similar approach is commonly used by researchers to ensure sufficient sample size for model estimation (e.g., Chen and Chen, 2011; Islam et al., 2014; Milton et al., 2008; Uddin and Huynh, 2017). The above three injury severity levels were coded in Eqs. (2) and (3) as follows: 1 for major injury, 2 for minor injury, and 3 for no injury.

From the HSIS dataset, 44 factors were selected as explanatory variables due to their availability and suitability in explaining injury severity of HAZMAT truck crashes. These factors were broadly classified into (1) occupant characteristics, (2) crash characteristics, (3) vehicle characteristics, (4) roadway characteristics, (5) environmental characteristics, and (6) temporal characteristics. The observations with missing values were eliminated from the final dataset used for model estimation. Table 1 presents the explanatory variables, which are cross-tabulated with the injury severity levels. The percentages next to the major, minor, and no injury columns are row percentages while those in the last column are column percentages. A few points are worth mentioning from the table. Although the total number of crashes occurring in rural locations was lower than that of urban locations, major injuries were more prevalent in rural locations (15.6% vs. 4.8%). Also, lighting condition variables were found to substantially differ in major injuries to occupants. They were involved in more major injuries under dark-unlighted conditions (15.6%) compared to under daylight (3.1%) and under dark-lighted (8.7%) conditions. The injuries sustained by occupants were more severe in crashes occurring on interstate highways.

The final dataset consists of 1173 observations. Each observation is a crash record that records the injury severity of the most severely injured occupant, along with occupant, crash, vehicle, roadway, environmental, and temporal characteristics. Hence, the dependent variable is the injury severity of the most severely injured occupant of the HAZMAT truck involved in the crash; the occupant could be either the driver or the passenger. As explained, the dependent variable had three levels of injury severity: major injury, minor injury, and no injury. There were 71 observations involving major injury (6.1%), 696 observations involving minor injury (59.3%), and 406 observations involving no injury (34.6%).

Results and discussions

The fixed-parameters ordered probit model was estimated using the maximum likelihood method, and the random-parameters model was estimated using the *simulated* maximum likelihood method. The statistical software NLOGIT (version 5) was used to estimate both models. During the model development process, variables were retained in the specification if they have t-statistics corresponding to the 90% confidence level or higher on a two-tailed t-test. This study considered the normal, lognormal, triangular, and uniform distributions for the random parameters. However, only the normal distribution was found as statistically significant. Hence, the normal distribution was used in the random-parameters model. Two hundred Halton draws were utilized, which has been found to produce accurate parameter estimates by other researchers (Islam and Hernandez, 2013a,b; Milton et al., 2008; Pahukula et al., 2015). In case of random-parameters model, the parameters were retained if their standard deviations have t-statistics corresponding to the 90% confidence level or higher. Furthermore, to avoid the inclusion of highly correlated variables in the model, a correlation matrix was estimated and the results indicate that none of the variables have a correlation value of more than ±0.20. Table 2 summarizes the estimation results for both fixed- and random-parameters ordered probit models along with average direct pseudo-elasticities of the parameters. Note that elasticities were calculated from the random-parameters model results. A negative coefficient for an explanatory variable indicates that if the variable is true (i.e., has value 1), it will result in increased injury severity while all other variables remaining constant, since higher injury severity has lower order in the data. Six parameters, older occupant (60 and over), male occupant, rural location, dark-unlighted, dark-lighted, and higher speed limit ($\geq$65 mph), were found to be random with statistically significant standard deviations.

Once the models were developed, a likelihood ratio test was performed to check the suitability of separate models for single- and multi-vehicle crashes over one aggregate model as follows (Washington et al., 2011).

Table 1
Descriptive statistics of the explanatory variables.

Explanatory variable	Major injury		Minor injury		No injury		Total	
Total	71		696		406		1173	
Occupant characteristics								
Age								
Less than 18	5	2.0%	80	31.3%	171	66.7%	256	21.8%
18–24	23	8.8%	151	57.6%	88	33.6%	262	22.4%
25–59	32	6.2%	389	75.4%	95	18.4%	516	44.0%
Over 60	11	7.9%	76	54.7%	52	37.4%	139	11.8%
Gender								
Male	64	9.4%	403	59.2%	214	31.4%	681	58.1%
Female	7	1.4%	293	59.6%	192	39.0%	492	41.9%
Driver								
Yes	41	7.8%	440	83.3%	47	8.9%	528	45.0%
No	30	4.7%	256	39.7%	359	55.6%	645	55.0%
Crash characteristics								
Location type								
Rural	42	15.6%	157	58.2%	71	26.3%	270	23.0%
Urban	29	4.8%	539	58.3%	335	36.9%	903	77.0%
Collision type								
Rear-end	2	0.5%	227	58.4%	160	41.1%	389	33.2%
Right-angle	18	6.3%	171	59.3%	99	34.4%	288	24.6%
Object	12	6.4%	124	66.3%	51	27.3%	187	15.9%
Lighting condition								
Daylight	21	3.1%	421	61.5%	242	35.4%	684	58.3%
Dark-unlighted	22	15.6%	81	57.4%	38	27.0%	141	12.0%
Dark-lighted	23	8.7%	162	61.4%	79	29.9%	264	22.5%
Vehicle characteristics								
Vehicle movement								
Going straight	43	8.3%	289	56.0%	184	35.7%	516	44.0%
Making a turn	5	2.6%	101	53.2%	84	44.2%	190	16.2%
Seat belt	19	4.8%	220	55.8%	155	39.4%	394	33.6%
Number of vehicle								
Single vehicle	51	12.6%	257	63.8%	95	23.6%	403	34.4%
Multi vehicle	20	2.6%	439	57.0%	311	40.4%	770	65.6%
Roadway characteristics								
Highway type								
Interstate	45	8.5%	316	59.6%	169	31.9%	530	45.2%
Non-interstate	26	4.0%	380	59.1%	237	36.9%	643	54.8%
Number of lanes								
≤ 4	46	6.1%	405	53.5%	306	40.4%	757	64.5%
>4	25	6.0%	291	70.0%	100	24.0%	416	35.5%
AADT								
$\leq$15,000	14	6.4%	162	74.0%	43	19.6%	219	18.7%
15,001–50,000	15	3.3%	252	54.9%	192	41.8%	459	39.1%
50,001–100,000	12	6.6%	104	57.1%	66	36.3%	182	15.5%
>100,000	30	9.6%	178	56.9%	105	33.5%	313	26.7%
Speed limit								
<45	3	1.9%	95	59.3%	62	38.8%	160	13.6%
45–60	31	8.1%	216	56.1%	138	35.8%	385	32.8%
≥ 65	37	5.9%	385	61.3%	206	32.8%	628	53.6%
Surface condition								
Dry	44	5.3%	474	57.3%	309	37.4%	827	70.5%
Wet	21	9.8%	116	54.2%	77	36.0%	214	18.2%
Environmental characteristics								
Weather condition								
Inclement	27	6.0%	159	59.8%	97	34.2%	283	24.1%
Clear	41	4.7%	523	60.3%	303	35.0%	867	73.9%
Terrain type								
Flat	34	4.5%	441	58.3%	282	37.2%	757	64.5%
Rolling	16	6.1%	168	64.1%	78	29.8%	262	22.3%
Temporal characteristics								
Time of day								
7 AM–9:59 AM	6	3.6%	107	63.7%	55	32.7%	168	14.3%
10 AM–3:59 PM	12	2.9%	284	69.8%	111	27.3%	407	34.7%
4 PM–6:59 PM	4	1.6%	150	61.5%	90	36.9%	244	20.8%
7 PM–6:59 AM	49	13.8%	155	43.8%	150	42.4%	354	30.2%
Day of week								
Weekday	44	5.5%	490	61.8%	259	32.7%	793	67.6%
Weekend	27	7.1%	206	54.2%	147	38.7%	380	32.4%

Table 2
Parameter estimates and elasticities.

Explanatory variable	Parameter estimates		Average direct pseudo-elasticities[‡]		
	Fixed-parameters model	Random-parameters model	Major injury	Minor injury	No injury
Occupant characteristics					
Age (1 for age group of over 60 years, 0 otherwise)	0.26**	0.58*** (2.00***)[†]	−101.1%	−21.2%	101.8%
Male (1 if male, 0 otherwise)	−0.13*	−0.06* (0.49***)[†]	18.0%	1.8%	−8.5%
Driver (1 if driver, 0 otherwise)	−1.17***	−2.25***	908.7%	59.9%	−297.1%
Crash characteristics					
Read-end (1 if rear-end collision, 0 otherwise)	0.39***	0.53***	−141.6%	−17.5%	84.4%
Object (1 if collision with an object, 0 otherwise)	0.41***	0.50***	−100.1%	−17.6%	84.7%
Rural (1 if crash occurred at a rural location, 0 otherwise)	−0.35***	−0.53*** (1.90***)[†]	303.3%	14.0%	−68.2%
Dark-unlighted (1 if crash occurred under dark-unlighted condition, 0 otherwise)	−0.33**	−0.54*** (1.65***)[†]	370.7%	13.2%	−64.5%
Dark-lighted (1 if crash occurred under dark-lighted condition, 0 otherwise)	−0.43***	−0.52*** (1.14***)[†]	291.7%	13.7%	−66.3%
Vehicle characteristics					
Making a turn (1 if truck was making a turn, 0 otherwise)	0.47***	0.58***	−110.6%	−20.9%	100.5%
Roadway characteristics					
Non-interstate (1 if crash occurred on non-interstate highway, 0 otherwise)	0.31***	0.32***	−112.9%	−9.7%	46.7%
Speed limit (1 if speed limit $\geqslant$ 65 mph, 0 otherwise)	0.27***	0.24*** (0.42***)[†]	−81.6%	−7.3%	35.4%
Environmental characteristics					
Flat terrain (1 if crash occurred on flat terrain, 0 otherwise)	0.22***	0.38***	−158.0%	−11.2%	53.9%
Temporal characteristics					
Weekday (1 if crash occurred on a weekday, 0 otherwise)	−0.19**	−0.33***	90.5%	10.6%	−50.9%
Constant	2.10***	3.95***			
Threshold 1, μ_1	2.42***	4.30***			
Log-likelihood at zero, $LL(0)$	−993.17	−993.17			
Log-likelihood at convergence, $LL(\beta)$	−818.27	−770.35			
Chi-square	349.8	445.6			
Pseudo R-square	0.18	0.22			
AIC	1,666.5	1,582.7			
BIC	1,742.6	1,689.1			
Number of observations, N	1,173	1,173			

*** Significant at the 99% confidence level.
** Significant at the 95% confidence level.
* Significant at the 90% confidence level.
† The value in parenthesis is the standard deviation of the random parameter distribution.
‡ Average direct pseudo-elasticities are calculated from the random-parameters model.

$$LR_{Full} = -2[LL_{Full}(\beta^{Full}) - LL_{Single}(\beta^{Single}) - LL_{Multi}(\beta^{Multi})] \tag{6}$$

where $LL_{Full}(\beta^{Full})$ is the log-likelihood at convergence of the full model (−770.35), $LL_{Single}(\beta^{Single})$ is the log-likelihood at convergence of the single-vehicle crash model (−388.34) and $LL_{Multi}(\beta^{Multi})$ is the log-likelihood at convergence of the multi-vehicle crash model (−386.90) using the same variables included in the full model. Note that log-likelihood values are from random-parameters model. The test statistic (LR_{Full} = 9.78) is χ^2 distributed, with degrees of freedom equal to the summation of the number of estimated parameters in both single- and multi-vehicle crash models minus the number of estimated parameters in the full model. The null hypothesis here is that there is no difference in the parameter values between the full model and separate models. The test statistic with 21 degrees of freedom resulted in a value less than the critical value at the 90% confidence level (χ^2 = 29.62), indicating that the single- and multi-vehicle models do not have statistically different parameters.

Model comparison

Following the methodology articulated in Washington et al. (2011), a likelihood ratio test was performed to compare the fixed- and random-parameters ordered probit models. The null hypothesis of the test is that the fixed-parameters model is statistically equivalent to the random-parameters model. The likelihood ratio is as follows (Washington et al., 2011).

$$LR = -2[LL_{Fixed}(\beta^{Fixed}) - LL_{Random}(\beta^{Random})] \tag{7}$$

where $LL_{Fixed}(\beta^{Fixed})$ = log-likelihood at convergence of the fixed-parameters model (−818.27) and $LL_{Random}(\beta^{Random})$ = log-likelihood at convergence of the random-parameters model (−770.35). The chi-square test statistic (LR = 95.84) with six degrees of freedom resulted in a value greater than the critical value at the 99.99% confidence level (χ^2 = 27.86). The null hypothesis is rejected, which indicates the validity of the random-parameters model over the corresponding fixed-parameters model. Additionally, to compare the goodness-of-fit of the models, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Pseudo R-square (R^2) were computed. Given the both models fit on the same dataset, the model with lower AIC and BIC, and higher R^2 is considered to outperform the other one. Table 2 suggests that the random-parameters model has lower AIC (1582.7 vs. 1666.5), lower BIC (1689.1 vs. 1742.6), and higher R^2 (0.18 vs. 0.22). Hence, the random-parameters model has a better fit than the fixed-parameters model.

Occupant characteristics

Considering the specific estimation results presented in Table 2, older occupant (age 60 and over) was found as a significant factor for crash injury severity. This parameter is random and normally distributed, with a mean 0.58 and a standard deviation 2.00. Given these estimates, 38.6% of the observations have parameter values less than 0 and 61.4% greater than 0. This implies that for more than half of the observations, older occupants were found to be involved in less severe injuries. The elasticities demonstrated a 101.1% decrease in major injuries, 21.2% decrease in minor injuries, and 101.8% increase in no injuries for the older occupants. The occupant age variable being significant with random parameter suggests that there is unobserved heterogeneity in HAZMAT involved crashes, may be due to the underreporting of the level of injury severity by highway patrol officers (Duncan et al., 1998). Islam and Hernandez (2013a) found that occupants aged between 55 and 65 were more likely to be severely injured. Uddin and Huynh (2017) found that truck occupants of the above age range had higher probability of minor injuries under daylight, and had lower probability of major and minor injuries under dark-lighted conditions in rural locations.

Male occupant variable was found to be random and normally distributed with a mean −0.06 and a standard deviation 0.49. The estimates suggest that for 54.9% of the observations the parameter values were less than 0. This suggests that slightly more than half of the observations resulted in more severe injuries to male occupants and slightly less than half resulted in less severe injuries. This finding is contrary to that of Abdel-Aty (2003) and Islam and Hernandez (2013a), and it is due to the fact that male occupants had higher proportion of major injuries than female in the sample (9.4% for male and 1.4% for female). The likelihood of major injuries for male occupants was found to increase by 18.0% and the likelihood of no injuries was found to decrease by 8.5%.

The occupant being the driver was found to result in more severe injuries. In fact, being the driver had the highest effect on the crash severity outcomes. The probability of major injury for a driver was increased by 908.7%, the probability of minor injury was increased by 59.9%, and the probability of no injury was decreased by 297.1%. Zhu and Srinivasan (2011) reported that older, African-American, and taller truck drivers are vulnerable to more severe injury crashes. Chen and Chen (2011) found that the likelihood of older truck drivers being involved in a incapacitating/fatal injury increases with single-vehicle crashes and decreases with multi-vehicle crashes.

Crash characteristics

Rear-end collisions were less likely to result in severe injuries to occupants. The probability of major injuries was found to decrease by 141.6% and the probability of no injuries was found to increase by 84.4% in rear-end collisions. This finding is intuitive since rear-end collisions mostly cause vehicle structural damages. Also, this finding is consistent with the study by Uddin and Huynh (2017); they found that rear-end collisions decreased the probability of minor injuries under urban dark-unlighted conditions and possible/no injuries under urban dark-lighted conditions.

When a truck hits an object, occupants were less likely to sustain severe injuries. Specifically, the occupants were associated with a decrease in the risk of major injuries by 100.1% and an increase in the risk of no injuries by 84.7%. Khorashadi et al. (2005) reported that truck hitting an object decreased the probability of severe injuries for drivers by 34%. Islam et al. (2014) found that the chance of major injuries for drivers in both rural single- and rural multi-vehicle crashes increased when a truck hit an object. Uddin and Huynh (2017) found that hitting an object decreased the probability of minor injuries for occupants under rural dark-lighted, urban daylight, and urban dark-lighted conditions.

The variable indicating crashes occurring in rural locations was found as significant with a random parameter that is normally distributed with a mean −0.53 and a standard deviation 1.90. This implies that 61.0% of the observations have parameter values less than 0 and 39% greater than 0. For more than half of the observations where crashes occurred in rural locations occupants had more severe injuries. The crashes in rural locations were associated with higher likelihood of major injuries (303.3%) and lower likelihood of no injuries (68.2%) for occupants compared to that of urban locations. One possible explanation could be the fact that emergency response time is slower in rural areas. This finding is in line with the findings of Chang and Mannering (1999) and Islam and Hernandez (2013b).

The findings from the analysis for lighting condition variables are intuitive. The elasticity results indicate that the probability of major injuries for occupants increased under both dark-unlighted (370.7%) and dark-lighted (291.7%) conditions. Under dark conditions, roadway visibility is lower, which may increase the chance of collisions. These findings related to lighting variable are consistent to that prior truck safety studies (Cerwick et al., 2014; Duncan et al., 1998; Islam and Hernandez, 2013b; Khorashadi et al., 2005; Zhu and Srinivasan, 2011). The parameter for dark-unlighted condition was found as random and normally distributed with mean −0.54 and standard deviation 1.65. Given these estimates, 62.8% of the observations under dark-unlighted conditions were found to be involved in more severe injuries and 37.2% in less severe injuries to the occupants. Also, the parameter for dark-lighted condition was found as random and normally distributed with a mean −0.52 and a standard deviation 1.14. This implies that 67.6% of the observations under dark-lighted conditions were found to be involved in more severe injuries and 32.4% in less severe injuries to the occupants.

Vehicle characteristics

HAZMAT crashes, where a truck was making a turn, were found to be associated with decreased likelihood of major injuries (110.6%) and increased likelihood of no injuries (100.5%) for occupants. One possible reason could be the fact that trucks generally slow down while making a turn. Thus, the chance of high-impact collision reduces. Khorashadi et al. (2005) reported that when a truck was making a turn the probability of fatal injuries for drivers decreased by 87.2%. Chang and Mannering (1999) found that the probability of possible injuries for occupants increased during right turns, and the probability of property damage only and possible injuries decreased during left turns.

Roadway characteristics

For crashes occurring on non-interstate highways, the likelihood of major injuries decreased by 112.9% and the likelihood of no injuries increased by 46.7% for the occupants. This may be because of lower traffic volume on non-interstate highways. However, this finding is contrary to that of Zhu and Srinivasan (2011).

Higher speed limit ($\geq$65 mph) variable was found as random and normally distributed with a mean 0.24 and a standard deviation 0.42. Given these estimates, 28.4% of the observations have parameter values less than 0 and 71.6% greater than 0. This implies that majority of the observations had less severe injuries to the occupants when crashes occurred on highways with higher speed limit. Specifically, the likelihood of major injuries for occupants decreased by 81.6% and the likelihood of no injuries increased by 35.4%. One possible explanation could be that drivers are more cautious in high speed limit highways, especially the drivers of HAZMAT trucks. This result is consistent with prior findings (Chang and Mannering, 1999; Zhu and Srinivasan, 2011).

Environmental characteristics

Among environmental characteristics considered, only flat terrain variable was significant. It was found that HAZMAT crashes occurring on flat terrain had lower probability of major injuries (158.0%) and higher probability of no injuries (53.9%) to the occupants. This could be explained by high visibility on flat terrain, which in turn helps drivers to make last second maneuvering (if necessary) and to avoid impending collisions.

Temporal characteristics

HAZMAT truck crashes occurring during weekdays were found to be more severe than weekend crashes. The likelihood of major injuries for occupants increased by 90.5%, while the likelihood of no injuries decreased by 50.9%. One possible reason could be the fact that roadways carry higher volumes of traffic during weekdays and consequently higher chance of trucks being involved in crashes in general. This finding is in line with the finding of Islam and Hernandez (2013a).

Conclusions

This paper analyzed injury severity of crashes involving HAZMAT large trucks in the state of California through the development of fixed- and random-parameters ordered probit models using crash data from 2005 to 2011. Three severity levels based on the injury severity sustained by the occupants were defined: major injury, minor injury, and no injury. The random-parameters model was developed to account for unobserved effects related to occupant, crash, vehicle, roadway, environmental, and temporal factors not present in the data. The results showed a consistent pattern for the sign of the variables in both the fixed- and random-parameters models. However, a likelihood ratio test suggested that the random-parameters model is statistically superior than the fixed-parameters model.

The results of the analyses identified several risk factors at occupant, crash, vehicle, roadway, environmental, and temporal levels that contribute to injury severity. The occupants being male, truck drivers, crashes occurring in rural locations, under dark-unlighted, under dark-lighted conditions, and on weekdays were associated with increased probability of major injuries; these findings can be used to develop policies to reduce risk of injuries from HAZMAT truck-involved crashes. In contrast, the older occupants (age 60 and over), truck making a turn, rear-end collision, collision with an object, crashes occurring on non-interstate highway, higher speed limit highway ($\geq$65 mph), and flat terrain were associated with decreased probability of major injuries.

This study has several limitations which should be taken into account when applying the findings. The first is that the crash data came from a single U.S. state. Second, the factors investigated were limited to those available in the HSIS database. The findings would be more generalizable if the dataset had crashes from multiple states and could be linked to other databases. Lastly, the findings from this study cannot be used to make recommendations or develop policies specifically for HAZMAT-designated routes.

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