Injury Severity Analysis of Commercially-Licensed Drivers in Single-Vehicle Crashes: Accounting for Unobserved Heterogeneity and Age Group Differences

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Abstract

This study analyzes the injury severity of commercially-licensed drivers involved in single-vehicle crashes. Considering the discrete ordinal nature of injury severity data, the ordered response modeling framework was adopted. The moderating effect of driver's age on all other factors was examined by segmenting the parameters by driver's age group. Additional effects of the different drivers' age groups are taken into consideration through interaction terms. Unobserved heterogeneity of the different covariates was investigated using the Mixed Generalized Ordered Response Probit (MGORP) model. The empirical analysis was conducted using four years of the Highway Safety Information System (HSIS) data that included 6,247 commercially-licensed drivers involved in single-vehicle crashes in the state of Minnesota. The MGORP model elasticity effects indicate that key factors that increase the likelihood of severe crashes for commercially-licensed drivers across all age groups include: lack of seatbelt usage, collision with a fixed object, speeding, vehicle age of 11 years or more, wind, night time, weekday, and female drivers. Also, the effects of several covariates were found to vary across different age groups.

Keywords: commercial driver license; injury severity; mixed generalized ordered response probit; heterogeneity; transportation safety

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1. Introduction

The U.S. Congress passed the Commercial Motor Vehicle Safety Act of 1986 to establish uniform standards for testing and licensing of operators of commercial motor vehicles (Commercial Motor Vehicle Safety Act of 1986, 1986). This Act prohibits any person from operating a Commercial Motor Vehicle (CMV) without a valid a commercial driver's license (CDL). This study aims to analyze factors contributing to the level of injury severity sustained by commercially-licensed drivers involved in single-vehicle crashes. A MGORP model was adopted to investigate potential heterogeneous effects associated with the set of explanatory variables being investigated (Eluru et al., 2008). It was essential to consider the differences among various drivers' age groups for modeling injury severity outcomes of single-vehicle crashes involving CDL holders. For example, older drivers tend to have longer reaction times and likely to be more vulnerable in a crash occurrence. In contrast, younger drivers may have less driving experience and likely to drive aggressively compared to other age groups (Lee and Mannering, 2002). In this paper, we specifically analyzed potential heterogeneous effects due to "age" on the injury severity outcomes through segmenting the variable effects by drivers' age groups.

The Federal Motor Carrier Safety Administration (FMCSA) states that drivers are required to have a CDL in order to operate certain commercial vehicles since April of 1992 (FMCSA, 2014a). FMCSA has developed standards to be adopted by the different States when issuing commercial licenses. A CDL is issued when the potential driver passes a set of knowledge and skills tests administered by the State, which directly corresponds to the specific type of vehicle a driver is seeking to operate. Three types of CDLs are classified by FMCSA (Class A, B, and C) depending on the vehicle's gross weight and the different combinations of units or trailers. According to the U.S. Department of Transportation (USDOT), in 2013, there were approximately 3.9 million registered commercially-licensed drivers operating in the U.S. (FMCSA, 2014a). Between 2009 and 2013, there were approximately 650,000 commercially-licensed drivers involved in roadway crashes, although this statistic only accounts for large trucks and buses only (FMCSA, 2014b). In 2016 alone, there were approximately 165,000 commercial crashes that involved nearly 4,700 fatalities and more than 91,000 injuries (U.S. Department of Transportation, 2017). The economic impact is substantial; the FMCSA states that in 2011, commercial crashes costs equated to $87 Billion (adjusted to 2012 dollars) (Zaloshnja and Miller, 2002). However, the economic impacts of crashes involving commercially- licensed drivers are outside the scope of this study.

A review of the dataset utilized in this study reveals that CDL holders are involved in more than just crashes in commercial vehicles; to include privately owned passenger-vehicles; possibly outside of work hours. Regardless of the type of vehicle being operated, CDL holders are likely operating on the road for longer periods of times and for greater distances, which may lead to higher risks of fatigue; raising the possibility of crash occurrence compared to non-CDL holders (Park et al., 2017). CDL holders are individuals who possess a higher level of knowledge, experience, skills, and physical abilities compared to standard driver's license holders. Serious traffic violations committed by CDL holders can affect their ability to maintain their certification (FMCSA, 2014a). Due to the possible differences in behavior between both CDL and non-CDL holders and the different nature of crashes both categories may be involved in, this study aims to target all commercial and non-commercial crashes involving drivers who, at the time of the crash, held a valid commercial driver's license.

The primary reasons to focus on commercially-licensed drivers involved in single-vehicle crashes are threefold: (1) the characteristics of multi-vehicle crashes are potentially different, (2) a multi-vehicle crash involves interactions between a CDL holder and likely a non-CDL holder with possible behavioral differences, and (3) a separate study that accounts for the role of the driver's age in the interaction between multiple vehicles in a crash (CDL to CDL, or CDL to non-CDL) is needed. This study aims more to specify how commercial drivers involved in single-vehicle crashes interact with the roadway, vehicle, temporal, and environmental factors, while accounting for age group differences and possible heterogeneous effects of the risk factors. To our knowledge, this study would be the first to analyze injury severity of commercially-licensed drivers involved in single-vehicle crashes. This study attempts to contribute to the literature of CDL driver's safety by adopting econometric models to investigate possible contributing factors to the severity of drivers involved, while investigating potential unobserved heterogeneity in the covariates as well as the differences across age groups.

The remainder of this paper is structured as follows. A literature review is presented in the next section followed by the methodology section presenting an overview of the econometric approach adopted and its statistical interpretation. The data section presents the dataset utilized and the final estimation sample assembly process. The results section presents an overview of the estimation results, statistical measures-of-fit, elasticity effects, and implications of variables' effects and recommendations. Finally, the conclusion section provides an overall summary of this research along with major findings, limitations, and future scope of research.

2. Literature Review

Literature shows a number of past studies analyzed severity of single-vehicle crashes in different settings, while other studies analyzed single-vehicle versus multi-vehicle crashes (Geedipally and Lord, 2010, p.; Martensen and Dupont, 2013; Yu and Abdel-Aty, 2013). Various studies identified the different types of roadways where single-vehicle crashes have occurred (Gong and Fan, 2017a; Rusli et al., 2017a; Wu et al., 2016b; Xie et al., 2012). Other studies identified the effects of specific factors (for example: age, gender, time, curb, etc.) on the severity of a single-vehicle crash (Anderson and Searson, 2015; Gong and Fan, 2017a; Jiang et al., 2013; Kim et al., 2013; Martensen and Dupont, 2013; Wu et al., 2016a). Several studies identified the type-of-crash as a rollover crash for single-vehicles (Anarkooli et al., 2017; Bambach et al., 2013; Fréchède et al., 2011).

On the contrary, literature exclusively examining CDL holders irrespective of what type of vehicle being operated within the context of injury severity is scarce. Most of large truck or bus crash injury severity studies account for crashes only involving those types of vehicles, yet limited to reflect the remaining of all possible combinations of vehicle types in the commercial fleet (Al-Bdairi and Hernandez, 2017; Chang and Chien, 2013; Chang and Mannering, 1999; Chen and Chen, 2011; Dong et al., 2015; Duncan et al., 1998; Islam and Hernandez, 2013; Khattak and Targa, 2004; Khorashadi et al., 2005; Lemp et al., 2011; Pahukula et al., 2015; Wang and Shi, 2013; Zhu and Srinivasan, 2011a, 2011b). In terms of studies specifically addressing injury severity of CMV, one study used a cross-classified multilevel model to investigate the severity of CMVs while addressing heterogeneity among firms and regions (Park et al., 2017). Another study analyzed the medical condition and the severity of CMV drivers but not specifically in a single-vehicle crash setting (Laberge-Nadeau et al., 1996). Other studies addressed seatbelt usage among CMV drivers in Utah (Cook et al., 2008; Eby et al., 2002; Kim and Yamashita, 2007). Few studies addressed sleeping quality, duration, and patterns (Bunn et al., 2005; Chen et al., 2016; Hanowski et al., 2007; Lemke et al., 2016; Sparrow et al., 2016). Based on the review of the literature that focused on commercially-licensed drivers, a gap in the literature certainly exists with respect to injury severity analysis. So, additional research is needed to understand the factors that influence the injury severity of CDL holders in the event of a crash.

3. Methodology

Several different modeling methods have been employed to analyze crash severity data. Typically these methods can be grouped into two categories – unordered (Chang and Mannering, 1999; Holdridge et al., 2005; Savolainen and Mannering, 2007; Shankar et al., 1996; Ulfarsson and Mannering, 2004) and ordered (Eluru et al., 2008; Wang et al., 2010; Zhu and Srinivasan, 2011a). With respect to the unordered frameworks, the multinomial logit model has been widely used in injury severity literature. The multinomial logit model brings constraints such as the "independence of irrelevant alternatives (IIA)" which is, in the literature, known as the red bus/blue bus problem (McFadden, 1973). The multinomial logit model also ignores the natural ordering of injury severity outcomes which can account for misleading or inaccurate results.

In the ordered response framework (such as the ordered probit model), a single latent propensity function is assumed to be translated into the observed severity outcome depending on the value of the propensity function relative to threshold parameters (number of thresholds = number of possible severity outcomes – 1). The latent propensity function is specified as a function of different factors along with a stochastic component to account for all unobserved factors that influence injury severity. The parameters in the single propensity equation and the thresholds constitute the set of parameters that are estimated using methods such as the maximum likelihood (ML). An ordered probit model is constrained to find only one coefficient on each variable that is also in one direction, towards either higher or lower injury severity levels; a constraint that is relaxed by the MNL model. Eluru et al. (2008) extended the standard ordered response framework to develop Generalized Ordered Response (GOR) models that allow parameterization of the threshold parameters providing additional flexibility to the ordinal models (Eluru et al., 2008). So, it is not surprising that a recent comparison analysis of unordered and ordered frameworks that considers generalized version of ordered models found minor differences between the two models (Anowar et al., 2014).

Injury severity conditional on crash occurrence can depend on numerous factors all of which are most certainly not observed in crash databases. These unobserved factors can moderate the influence of other observed covariates in the model leading to variation in the parameter effects across different observations. These unobserved variations are referred to as "unobserved heterogeneity", which is of considerable importance in injury severity analysis. One important feature of the MGORP model is that it addresses possible heterogeneity in covariates. Mannering et al. (2016) describes this issue in greater detail and present alternate modeling methods available in the literature for handling the problem (Mannering et al., 2016). Among these methods, the random parameters approaches are the most prominent.

Consistent with the recommendation of Eluru et al (2008), we adopted the Mixed Generalized Ordered Probit model to explore the effects of several contributing factors on the injury severity levels of commercially-licensed drivers involved in single-vehicle crashes (Eluru et al., 2008). For comparison reasons we initially estimated an ORP model, which also served as a starting point for developing the MGORP model. A brief overview of the MGORP model follows.

Let $\mathrm{n}(\mathrm{n}=1,2,\dots,\mathrm{N})$ be an index that represents occupants and $\mathrm{i}(\mathrm{i}=1,2,\dots,\mathrm{I})$ is the index representing injury severity categories. In the context of this study, index i will take the value "no injury" $(\mathrm{i}=1)$, "injury" ($i = 2$), and "severe injury" ($i = 3$). The MGORP model starts as a standard ORP. The equation system for the ORP model is (McKelvey and Zavoina, 1975):

$$y_n^* = \beta' X_n + \varepsilon_n$$

$$y_n = i \text{ if } (\psi_{i-1} < y_n^* < \psi_i) \quad (1)$$

where y_n^* is the latent propensity for occupant n in a given crash, which is translated into observed severity outcomes y_n by threshold parameters ψ_i. X_n is $K \times 1$ vector of covariates and β is the corresponding $K \times 1$ vector of coefficients; $\psi_i's$ are threshold parameters; $\psi_0 = -\infty$ and $\psi_{I+1} = \infty$. ε_n is a random error term capturing the effects of unobserved factors on the injury severity propensity. For model identification purposes, this error term ε_n is assumed to be independently and identically standard normal distributed across the crashes which leads to the ordered probit model (ORP). The model structure requires that the thresholds to be strictly ordered for the partitioning of the latent risk propensity measure into the ordered injury severity categories ($\text{i.e.}, -\infty < \psi_1 < \psi_2 < \cdots < \psi_{I-1} < \infty$) for each occupant n. The enhancement of the ORP model to a MGORP is characterized by the enabling β vector and ψ thresholds to vary across observations. This is accomplished through subscripting these parameters with the index n. The MGORP equation system can then be written as follows:

$$y_n^* = \beta'_n X_n + \varepsilon_n$$

$$y_n = i \text{ if } \left(\psi_{n,i-1} < y_n^* < \psi_{n,i}\right) \quad (2)$$

To account for unobserved heterogeneity, the β_n vector is assumed to a realization from a multivariate normal distribution with mean β and covariance Σ. Now, Equation (2) can be re-written as follows:

$$y_n^* = \beta_n X_n + \tilde{\varepsilon}_n \text{ where } \tilde{\varepsilon}_n \sim N(0, X_n' \Sigma X_n)$$

$$y_n = i \text{ if } \left(\psi_{n,i-1} < y_n^* < \psi_{n,i}\right) \quad (3)$$

Also, a specific non-linear functional form was used for parameterizing thresholds to ensure that the ordinal criterion is met ($-\infty < \psi_{n,1} < \psi_{n,2} < \cdots < \psi_{n,I-1} < \infty$) for each driver n:

$$\psi_{n,i} = \psi_{n,i-1} + \exp\left(\alpha_{n,i} + \gamma'_{n,i} Z_{ni}\right) \quad (4)$$

where Z_{ni} is a set of exogenous variables associated with the ith threshold excluding the constant; $\gamma_{n,i}$is the corresponding vector of coefficients, and $\alpha_{n,i}$ is a parameter associated with injury severity level $i = 1,2,\ldots,I-1$. $\psi_{n,1}$ is specified as $\exp(\alpha_1)$ for identification reasons. Moreover, $\gamma_{n,i}$ vector is assumed a realization from a multivariate normal distribution with mean γ_i and covariance Ω_i. Let γ_n and γ be the vertically stacked column vectors of all γ_{ni} and γ_i vectors.

The probability of observed injury severity i of occupant n conditional on γ_n is given by

$$P_n(i|\gamma_n) = \Phi\left(\frac{\psi_{n,i}-\beta'_n X_n}{\sqrt{X'_n \Sigma X_n}}\right) - \Phi\left(\frac{\psi_{n,i-1}-\beta'_n X_n}{\sqrt{X'_n \Sigma X_n}}\right) \quad (5)$$

The unconditional probability can be obtained by integrating out the random components of γ_n using simulation. The resulting model parameters were estimated using the maximum simulated likelihood (MSL) inference approach and 150 Halton draws (Bhat, 2001).

In addition to direct effect on severity outcomes, driver's age can have moderating influence on the effect of several covariates. Aging in general is directly related to losing some of the abilities a driver once had; however this happens with varying degrees across the population. Age as a number may not contribute much as a modeling variable, yet it can be concluded that the younger age group is more uniform than the older age group, with some of the older driver population being able to drive and function with medical impairment (Meuser et al., 2009). The importance of accounting for heterogeneity with age was shown in previous studies for pedestrians (Kim et al., 2010).

In addition to exploring heterogeneity in the different covariates through the random parameter framework of the MGORP model, we further addressed heterogeneity due to "age" through interaction terms between age groups (driver age groups: 16–24, 25–64, 65+) and all other covariates. An interaction term is created by multiplying the age group indicator with each of the covariates. Interaction variables represent a complexity of their own and therefore, filling the model with interaction terms can potentially yield a complex model that is difficult to interpret. So, interaction terms were kept to a minimum and only when found statistically significant and intuitively meaningful.

Differential impacts of the independent variables on the severity level were examined and the final specification for the presented model was based on a logical process of building a standard ORP, followed by the development of a generalized ordered response probit (GORP) model that allows each variable's effect to vary across observations while removing the statistically insignificant variables and combining other variables when their effects were statistically equal. Also, we extensively tested for potential unobserved heterogeneity effects of the injury severity determinants on the latent injury risk propensity due to unobserved factors. Thus, our final model specification became a partially segmented mixed generalized ordered response probit (MGORP) model. It terms of investigating the potential effects imposed by the drivers' age groups, we followed a systematic approach of interacting all statistically significant variables with each of the three age groups specified in this study. Final modeling process, simulation, and elasticity calculations for MGORP were carried out in Gauss programming language that is specifically suited for econometric modeling (Gauss 15). R statistical software was used for initial modeling process (ORP and GORP) and variable selection. SAS 9.4 statistical analysis software was also utilized for data cleaning and descriptive statistics.

4. Data

Data on commercially-licensed drivers in single-vehicle crashes was collected from all reported crashes in the State of Minnesota occurred during the years 2012-2015. In this paper, we define a crash as a roadway single-vehicle accident involving a motorized vehicle being operated by a commercially-licensed driver. In the remainder of this paper, "crash" and "driver" will refer to a single-vehicle crash involving a vehicle operated by a driver who is commercially-licensed. Data was obtained from the HSIS database and an initial review of the dataset revealed 7,165 single-vehicle crashes involving commercially-licensed drivers. Upon removing incomplete observations and excluding crashes involving pedestrians, motorcycles, and similar-in-nature non-vehicular motorized or non-motorized transportation means, the final dataset contained 6,427 unique single-vehicle crashes involving commercially-licensed drivers. In order to explore the dataset descriptively, it was categorized into age groups. Young drivers were those under 25 years old (490 observations – 7.62%), mid-age drivers ranged from 25-64 years old (5366 observations – 8.88%), and older drivers were those of age 65 years old and above (571 observations – 83.49%).

Table 1 presents the frequency distribution and number of observations of key variables classified by injury severity levels. Injury severity levels (dependent variable) of commercially-licensed drivers were initially represented in the original dataset with categories that followed the KABCO scale where: K=killed, A=incapacitating injury, B=non-incapacitating injury, C=possible injury, and O=no injury. While this research aims to investigate the injury severity levels of drivers, including added interactions of age groups with the different covariates can considerably reduce the frequency of some of the interacted covariates within each of the injury severity levels depicted. Due to both the specific nature of the observations in this study (CDL drivers) compared to an injury severity study for all drivers (non CDL or both CDL and non CDL combined), and the higher levels of training and precision of commercial drivers relative to standard driver license holders, it was not surprising the lower levels of higher injury severity outcomes in the dataset utilized. Therefore, and due to the initial lower frequency of some of the higher severity levels, some of the severity categories were combined to be able to balance the frequency of observations within each severity category. Combining injury severity categories will provide more confidence in the integrity of this research while obtaining a sound model with unbiased results. The combined injury severity categories are shown in Table 1. Fatal, incapacitating, and non-incapacitating severity levels were combined into one severity level referred to as "Injury" (I). "Possible injury" (PI), and "no injury" (NI) categories were kept as is. Similarly, Table 2 presents frequency distributions and number of observation of key variables classified by classified by the different age groups. Both Table 1 and Table 2 also present the percent of each category of each variable across injury severity levels and age groups respectively while also providing the row percent for all variables.

TABLE 1 Descriptive statistics for key variables classified by injury severity

Frequency
Percent
Row (%)

NI = No Injury
PI = Possible Injury
I = Injury

Explanatory Variable	Injury Severity NI	PI	I	Total
Driver age				
Young	385	42	63	490
< 25 years	5.99	0.65	0.98	7.62
	78.57	8.57	12.86	
Mid-age	4281	473	612	5366
25-64 years	66.61	7.36	9.52	83.49
	79.78	8.81	11.41	
Old	460	52	59	571
>=65 years	7.16	0.81	0.92	8.88
	80.56	9.11	10.33	
Gender				
	370	45	85	500
Female	5.76	0.7	1.32	7.78
	74	9	17	
	4756	522	649	5927
Male	74	8.12	10.1	92.22
	80.24	8.81	10.95	
Seatbelt used				
	789	211	138	1138
No	12.28	3.28	2.15	17.71
	69.33	18.54	12.13	
	4337	356	596	5289
Yes	67.48	5.54	9.27	82.29
	82	6.73	11.27	
CDL out-of-state				
	3738	457	592	4787
No	58.16	7.11	9.21	74.48
	78.09	9.55	12.37	
	1388	110	142	1640
Yes	21.6	1.71	2.21	25.52
	84.63	6.71	8.66	

Explanatory Variable	Injury Severity NI	PI	I	Total
Collision with				
	758	15	49	822
Animal	11.79	0.23	0.76	12.79
	92.21	1.82	5.96	
Fixed	622	100	110	832
object	9.68	1.56	1.71	12.95
	74.76	12.02	13.22	
	3746	452	575	4773
Other	58.29	7.03	8.95	74.26
	78.48	9.47	12.05	
Contributing factor				
	810	139	184	1133
Distracted	12.6	2.16	2.86	17.63
	71.49	12.27	16.24	
Improper	528	52	70	650
move	8.22	0.81	1.09	10.11
	81.23	8	10.77	
	1413	76	125	1614
None	21.99	1.18	1.94	25.11
	87.55	4.71	7.74	
	1537	163	219	1919
Other	23.91	2.54	3.41	29.86
	80.09	8.49	11.41	
	838	137	136	1111
Speeding	13.04	2.13	2.12	17.29
	75.43	12.33	12.24	
Freeway				
	3854	469	589	4912
No	59.97	7.3	9.16	76.43
	78.46	9.55	11.99	
	1272	98	145	1515
Yes	19.79	1.52	2.26	23.57
	83.96	6.47	9.57	
	3854	469	589	4912

Explanatory Variable	Injury Severity NI	PI	I	Total
Two-lane				
	2615	244	334	3193
No	40.69	3.8	5.2	49.68
	81.9	7.64	10.46	
	2511	323	400	3234
Yes	39.07	5.03	6.22	50.32
	77.64	9.99	12.37	
Undivided				
	1295	108	159	1562
No	20.15	1.68	2.47	24.3
	82.91	6.91	10.18	
	3831	459	575	4865
Yes	59.61	7.14	8.95	75.7
	78.75	9.43	11.82	
Speed limit				
	1725	113	178	2016
< 55 mph	26.84	1.76	2.77	31.37
	85.57	5.61	8.83	
	3401	454	556	4411
>= 55 mph	52.92	7.06	8.65	68.63
	77.1	10.29	12.6	
Urban				
	2732	369	428	3529
No	42.51	5.74	6.66	54.91
	77.42	10.46	12.13	
	2394	198	306	2898
Yes	37.25	3.08	4.76	45.09
	82.61	6.83	10.56	
Surface condition				
	2736	368	442	3546
Dry	42.57	5.73	6.88	55.17
	77.16	10.38	12.46	
	2390	199	292	2881
Wet	37.19	3.1	4.54	44.83
	82.96	6.91	10.14	

TABLE 1 continued

Frequency
Percent
Row (%)

NI = No Injury
PI = Possible Injury
I = Injury

Explanatory Variable	CDL driver age group NI	PI	I	Total
Curved				
	3995	374	484	4853
No	62.16	5.82	7.53	75.51
	82.32	7.71	9.97	
	1131	193	250	1574
Yes	17.6	3	3.89	24.49
	71.86	12.26	15.88	
Vehicle age				
	2547	210	293	3050
<= 10 years	39.63	3.27	4.56	47.46
	83.51	6.89	9.61	
	2579	357	441	3377
> 10 years	40.13	5.55	6.86	52.54
	76.37	10.57	13.06	
Vehicle type				
	1048	114	178	1340
Car	16.31	1.77	2.77	20.85
	78.21	8.51	13.28	
Truck-	2257	220	258	2735
heavy duty	35.12	3.42	4.01	42.55
	82.52	8.04	9.43	
Truck-	1821	233	298	2352
light duty	28.33	3.63	4.64	36.6
	77.42	9.91	12.67	
School bus				
	4727	560	714	6001
No	73.55	8.71	11.11	93.37
	78.77	9.33	11.9	
	399	7	20	426
Yes	6.21	0.11	0.31	6.63
	93.66	1.64	4.69	
Day of week				
	4041	435	565	5041
Weekday	62.88	6.77	8.79	78.43
	80.16	8.63	11.21	
Day of week				
	1085	132	169	1386
Weekend	16.88	2.05	2.63	21.57
	78.28	9.52	12.19	
Weather				
	2528	324	378	3230
Clear	39.33	5.04	5.88	50.26
	78.27	10.03	11.7	
	1112	125	179	1416
Cloudy	17.3	1.94	2.79	22.03
	78.53	8.83	12.64	
	482	54	56	592
Rainy	7.5	0.84	0.87	9.21
	81.42	9.12	9.46	
	876	44	93	1013
Snowy	13.63	0.68	1.45	15.76
	86.48	4.34	9.18	
	128	20	28	176
Windy	1.99	0.31	0.44	2.74
	72.73	11.36	15.91	
Time of day				
	2889	312	408	3609
Daylight	44.95	4.85	6.35	56.15
	80.05	8.65	11.31	
	406	35	48	489
Dusk/dawn	6.32	0.54	0.75	7.61
	83.03	7.16	9.82	
	1831	220	278	2329
Night	28.49	3.42	4.33	36.24
	78.62	9.45	11.94	
Driver cited				
	4312	398	543	5253
No	67.09	6.19	8.45	81.73
	82.09	7.58	10.34	
	814	169	191	1174
Yes	12.67	2.63	2.97	18.27
	69.34	14.4	16.27	

TABLE 2 Descriptive statistics for key variables classified by age group

Frequency
Percent
Row (%)

Explanatory Variable	Young (< 25)	Mid (25-64)	Old (>=65)	Total
Injury severity				
No injury	385	4281	460	5126
	5.99	66.61	7.16	79.76
	7.51	83.52	8.97	
Possible injury	63	612	59	734
	0.98	9.52	0.92	11.42
	8.58	83.38	8.04	
Injury	42	473	52	567
	0.65	0.81	7.36	8.82
	7.41	83.42	9.17	
Gender				
Female	58	407	35	500
	0.90	6.33	0.54	7.78
	11.6	81.4	7	
Male	432	4959	536	5927
	6.72	77.16	8.34	92.22
	7.29	83.67	9.04	
Seatbelt used				
No	81	969	88	1138
	1.26	15.08	1.37	17.71
	7.12	85.15	7.73	
Yes	409	4397	483	5289
	6.36	68.41	7.52	82.29
	7.73	83.13	9.13	
CDL out-of-state				
No	352	3975	460	4787
	5.48	61.85	7.16	74.48
	7.35	83.04	9.61	
Yes	138	1391	111	1640
	2.15	21.64	1.73	25.52
	8.41	84.82	6.77	

Explanatory Variable	Young (< 25)	Mid (25-64)	Old (>=65)	Total
Collision with				
Animal	36	694	92	822
	0.56	10.80	1.43	12.79
	4.38	84.43	11.19	
Fixed object	56	694	82	832
	0.87	10.80	1.28	12.95
	6.73	83.41	9.86	
Other	398	3978	397	4773
	6.19	61.90	6.18	74.26
	8.34	83.34	8.32	
Contributing factor				
Distracted	89	925	119	1133
	1.38	14.39	1.85	17.63
	7.86	81.64	10.5	
Improper move	60	534	56	650
	0.93	8.31	0.87	10.11
	9.23	82.15	8.62	
None	81	1361	172	1614
	1.26	21.18	2.68	25.11
	5.02	84.32	10.66	
Other	158	1616	145	1919
	2.46	25.14	2.26	29.86
	8.23	84.21	7.56	
Speeding	102	930	79	1111
	1.59	14.47	1.23	17.29
	9.18	83.71	7.11	
Freeway				
No	385	4064	463	4912
	5.99	63.23	7.20	76.42
	7.84	82.74	9.43	
Yes	105	1302	108	4912
	1.63	20.26	1.68	23.57
	6.93	85.94	7.13	

Explanatory Variable	Young (< 25)	Mid (25-64)	Old (>=65)	Total
Two-lane				
No	229	2714	250	3193
	3.56	3.89	42.23	49.68
	7.17	85	7.83	
Yes	261	2652	321	3234
	4.06	41.26	4.99	50.32
	8.07	82	9.93	
Undivided				
No	94	1339	129	1562
	1.46	2.01	20.83	24.30
	6.02	85.72	8.26	
Yes	396	4027	442	4865
	6.16	62.66	6.88	75.70
	8.14	82.77	9.09	
Speed limit				
< 55 mph	140	1688	188	2016
	2.18	26.26	2.93	31.37
	6.94	83.73	9.33	
>= 55 mph	350	3678	383	4411
	5.45	57.23	5.96	68.63
	7.93	83.38	8.68	
Urban				
No	274	2918	337	3529
	4.26	5.24	45.40	54.91
	7.76	82.69	9.55	
Yes	216	2448	234	2898
	3.36	38.09	3.64	45.09
	7.45	84.47	8.07	
Surface condition				
Dry	279	2930	337	3546
	4.34	45.59	5.24	55.17
	7.87	82.63	9.5	
Wet	211	2436	234	2881
	3.28	37.90	3.64	44.83
	7.32	84.55	8.12	

TABLE 2 continued

Frequency Percent Row (%)

Explanatory Variable	Age Group Young (< 25)	Mid (25-64)	Old (>=65)	Total
Curved				
No	336 5.23 6.92	4063 63.22 83.72	454 7.06 9.36	4853 75.51
Yes	154 2.40 9.78	1303 20.27 82.78	117 1.82 7.43	1574 24.49
Vehicle age				
<= 10 years	195 3.03 6.39	2594 40.36 85.05	261 4.06 8.56	3050 47.46
> 10 years	295 4.59 8.74	2772 43.13 82.08	310 4.82 9.18	3377 52.54
Vehicle type				
Car	170 2.65 12.69	1048 16.31 78.21	122 1.90 9.1	1340 20.85
Truck-heavy duty	158 2.46 5.78	2390 37.19 87.39	187 2.91 6.84	2735 42.55
Truck-light duty	162 2.52 6.89	1928 30.00 81.97	262 4.08 11.14	2352 36.60
School bus				
No	481 7.48 8.02	5016 78.05 83.59	504 7.84 8.40	6001 93.37
Yes	9 0.14 2.11	350 5.45 82.16	67 1.04 15.73	426 6.63
Day-of-week				
Weekday	343 5.34 6.8	4230 65.82 83.91	468 7.28 9.28	5041 78.43

Explanatory Variable	Age Group Young (< 25)	Mid (25-64)	Old (>=65)	Total
Day-of-week				
Weekend	147 2.29 10.61	1136 17.68 81.96	103 1.60 7.43	1386 21.57
Weather				
Clear	269 4.19 8.33	2685 41.78 83.13	276 4.29 8.54	3230 50.26
Cloudy	96 1.49 6.78	1179 18.34 83.26	141 2.19 9.96	1416 22.03
Rainy	31 0.48 5.24	513 7.98 86.66	48 0.75 8.11	592 9.21
Snowy	76 1.18 7.5	844 13.13 83.32	93 1.45 9.18	1013 15.76
Windy	18 0.28 10.23	145 2.26 82.39	13 0.20 7.39	176 2.74
Time-of-day				
Daylight	245 3.81 6.79	3000 46.68 83.13	364 5.66 10.09	3609 56.15
Dusk/dawn	31 0.48 6.34	415 6.46 84.87	43 0.67 8.79	489 7.61
Night	214 3.33 9.19	1951 30.36 83.77	164 2.55 7.04	2329 36.24
Driver cited				
No	365 5.68 6.95	4389 68.29 83.55	499 7.76 9.5	5253 81.73
Yes	125 1.94 10.65	977 15.20 83.22	72 1.12 6.13	1174 18.27

5. Estimation Results

Table 3 presents the estimation results of the MGORP model. The first column of Table 3 presents the explanatory variables, while the second and third columns present two sets of variable coefficient parameters corresponding to the different injury severity levels. The second column presents each variable in the latent risk propensity function. The third column presents variables that entered the threshold specification function between the “possible injury” and “injury” outcomes. Positive (+) threshold parameter values indicate larger region of “possible injury” vs. “injury” under an injury severity probability curve (Eluru et al., 2008), while negative (-) parameter values indicate larger “injury” vs. “possible injury” outcomes. The respective t-values of the estimated coefficients are shown in parentheses. Table 3 also presents initial log-likelihood value, the log-likelihood value at convergence, the McFadden R2, and the total number of observations in the dataset. In the “variable” column, each variable found statistically significant is followed by its potential interactions with each of the three age groups. Variable names in the first column which are followed by a standard deviation (SD) (for example: female) indicate statistically significant unobserved heterogeneity in the corresponding parameter.

In the initial modeling process, each independent variable was regressed as a “standalone” variable to test for the statistical significance of its effect across all age groups, followed by its additional interaction effects across each individual age group. This partially segmented approach uncovers the differences imposed by the different age groups on each of the covariates initially found statistically significant in the MGORP model before the introduction of any interaction terms.

5.1. Driver characteristics

Relative to males, all female drivers (across all age groups) were associated with a higher injury propensity relative to no injury (female parameter: + 0.212). A positive threshold value for “female” indicated that females are likely to sustain possible injuries relative to injuries (+ 0.357). Perhaps the

TABLE 3 MGORP model results

Explanatory Variables		MGORP Injury Propensity	MGORP Threshold: PI | I
Driver			
Gender (base: male)			
Female		0.212 (1.353)	0.357 (2.13)
Standard deviation		0.802 (1.98)	
Seatbelt Usage (base: used)			
Not used		0.488 (7.48)	-0.392 (-4.43)
CDL origin state (base: in-state)			
Out-of-state		-0.253 (-3.54)	-0.110 (-1.16)
Accident			
Collision with (base: other)			
Animal		-1.267 (-4.43)	-
Standard deviation		0.757 (2.51)	
Fixed object		0.132 (1.93)	-
Contributing factor (base: none, improper move, other)			
Speeding		0.391 (5.05)	-0.121 (-1.26)
Distracted		0.129 (1.35)	0.241 (1.99)
Standard deviation		0.643 (2.32)	
Improper move	Young		-
	Mid-age	-0.096 (-1.11)	-
	Old		-
Freeway (base: not on freeway)			
On freeway		-1.599 (-2.84)	0.606 (2.56)
Standard deviation		2.193 (3.34)	
Roadway			
Number of lanes (base: multi-lane)			
Two-lane		-0.180 (-2.23)	-
Multi-lane	Young		
	Mid-age		
	Old	-0.233 (-1.43)	-
Roadway division (base: divided)			
Undivided		0.217 (2.50)	-
Undivided	Young		
	Mid-age		
	Old	0.217 (1.94)	-
Speed limit (base: ≥ 55 mph)			
< 55 mph		-0.602 (-8.37)	-
Area type (base: rural)			
Urban		-0.211 (-2.92)	0.121 (1.69)
Surface condition (base: dry)			
Wet		-0.352 (-5.81)	-0.121 (-1.49)

TABLE 3 Continued

		MGORP	
Explanatory Variables		**Injury Propensity**	**Threshold: PI | I**
Curvature (base: straight)			
Curved		0.300 (4.88)	0.157 (2.12)
Curved	Young		
	Mid-age		
	Old	0.201 (1.05)	-
Vehicle age (base: < 5 years, 5-10 years)			
> 10 years		0.100 (1.37)	-
Standard deviation		0.462 (2.31)	
Vehicle type (base: car, truck-light duty)			
Truck-heavy duty		-0.275 (-4.52)	-0.199 (-2.51)
Car	Young		
	Mid-age		
	Old	-0.240 (-1.26)	-
Truck-heavy duty	Young	-0.259 (-1.54)	-
	Mid-age		
	Old		
School bus involved (base: not involved)			
Involved		-0.588 (-4.29)	-
Temporal			
Weather (base: clear, cloudy, rain)			
Snow		-1.877 (-3.43)	0.634 (3.32)
Standard deviation		1.537 (3.53)	
Snow	Young		
	Mid-age	0.883 (2.59)	-
	Old		
Wind		0.226 (1.68)	0.208 (1.17)
Time-of-day (base: day, dusk/dawn)			
Night		0.052 (1.01)	-
Dusk/dawn	Young	-0.624 (-1.47)	-
	Mid-age		
	Old		
Day-of-week (base: weekend)			
Weekday		0.069 (1.18)	-
Constants			
Threshold 1 (no injury | injury)		-0.5135 (-2.92)	
Threshold 2 (injury | severe injury)		-0.333 (-3.39)	
Log-Likelihood at zero		-4,128.63	
Log-Likelihood at convergence		-3,684.02	
McFadden R^2		0.1077	
Number of observations		6,427	

female physiological and behavioral differences, compared to male, may contribute to the higher vulnerability to higher injury severity levels. Other studies on single-vehicle crashes (non-CDL) indicated similar results for both standard vehicles and large trucks (Anarkooli et al., 2017; Chen and Chen, 2011), although large trucks are only a portion of the CDL population. The female indicator was found to be heterogeneous around the mean of the estimated parameter with a t-statistic for the standard deviation of (+1.98).

The indicator variable for not wearing a seatbelt was found to be strongly associated with higher injury severity levels, indicated by the positive injury propensity value (+0.488) and a t-statistic of (+7.48). The negative threshold parameter, (-0.392) and a t-statistic of (-4.43), further indicated that a CDL driver would sustain an injury relative to possible injury. Being unrestrained within a vehicle likely leads to ejection or increases the chances for impacting other objects; both could have severe outcomes. Similar results were found in the literature for large truck injury severity studies (Chang and Chien, 2013; Chang and Mannering, 1999).

Out-of-state drivers were associated with lower injury propensities given the negative parameter of (-0.253) compared to in-state drivers. Although the negative threshold value for out-of-state driver indicated that in the event of a crash, a CDL driver would likely be injured. Out-of-state drivers are expected to be more cautious on unfamiliar roadways and likely paying additional attention to the specific geometrics of the road segment being crossed. According to past literature, higher severity levels were reported for single occupant truck-involved crashes when drivers resided within 15 miles on crash location, although not necessarily CDL holders (Chang and Mannering, 1999). On the contrary, other researchers reported lower severity levels for in-state drivers of large trucks (Islam and Hernandez, 2013).

5.2. Accident characteristics

Compared to colliding with other objects on the roadway, collision with an animal was found to be associated with lower injury propensity given the negative coefficient parameter of (-1.267); although this variable was found to be heterogeneous around the mean of the estimated parameter with a t-statistic for its standard deviation of (+2.51). Past studies indicted similar behavior for collisions with animals among truck drivers, but not necessarily commercially licensed drivers (Chen and Chen, 2011). On the contrary, a collision with fixed object was associated with severe outcomes for CDL drivers. Comparable results were found in the large truck injury severity literature (Zhu and Srinivasan, 2011a, 2011b).

Speeding was found to be highly significant across age groups, indicated by its positive injury propensity parameter (parameter: 0.391, t-value: 5.05). A negative threshold value indicated that speeding CDL holders will likely sustain severe outcomes. This result may encourage law enforcement to enforce higher penalties for those drivers found guilty of driving above speed limits. Similar results were found in studies for the severity of commercial motor vehicles (Park et al., 2017).

Among other contributing factors to a crash involving a CDL holder, distracted driving was associated with higher injury propensity in the event of a crash. Although this variable was found to be heterogeneous around the mean of the coefficient parameter. Zhu and Srinivasan (2011) found similar results for distracted driving (Zhu and Srinivasan, 2011b). Making an improper move among mid-age CDL holders was associated with the lowest injury propensity compared other age groups. Younger drivers are likely to lack experience, while older drivers may have longer reaction times to either making a maneuver or recovering back from it, in the case of a possible crash. Freeways as a crash environment was associated with lower risk propensities compared to non-freeways. CDL drivers are likely to sustain possible injuries rather than injuries. The "freeway" indicator was found to be heterogeneous with a t-value for its standard deviation of (+3.34). Compared to non-freeways, freeways have fewer distractions to drivers, mostly wider travel lanes, and fewer conflict points. Not specifically controlling for CDL drivers, past studies found that large truck crashes were more severe on freeways (Lemp et al., 2011; Zhu and Srinivasan, 2011a).

5.3. Roadway characteristics

Crashes on two-lane roadways were associated with lower injury propensities across all age groups (parameter: -1.180, t-value: -2.23). Additionally, age group interactions with "two-lanes" indicated that older drivers had the lowest risk compared to other age groups. Although these results may not just be specific to CDL drivers as a number of past studies also found that lower injury severities were associated with the decreased number of lanes in single vehicle crashes in both urban and rural settings (Gong and Fan, 2017a; Wu et al., 2016b). Although, a study of large-truck injury severity found that more lanes were less severe (Zhu and Srinivasan, 2011b).

Undivided roadways contributed significantly to higher severity outcomes indicted by the positive propensity (parameter: 0.217, t-value: 2.50) across all age groups, with the older driver associated with the highest risk compared to other age groups. This is logical as drivers on undivided roadways are likely exposed to opposing traffic, which increases distraction, compared to divided roadways. Similar studies that included both CDL and non-CDL holders found similar results in both single and multiple vehicle crashes (Kim et al., 2013; Morgan and Mannering, 2011).

Lower speed limits (less than 55 mph) contributed significantly to reduced injury severity outcomes across all age groups, as would be expected (parameter: -0.602, t-value: -8.37). Reduced speeds will always allow for more reaction time and careful maneuvers avoiding the occurrence of a crash.

Urban roadways were less severe for CDL drivers compared to rural roadways. This result is anticipated as urban roadways are likely associated with lower speeds, while rural roadways may pose higher risk, especially to vehicles involved in single-vehicle crashes such as running off the road and particularly at rural higher speeds. Past passenger-car and large truck studies have found similar results (Dong et al., 2015; Duncan et al., 1998).

Wet surface was associated with lower injury propensities across all age groups. Although in the event of a crash, the MGORP model negative threshold coefficient indicated severe outcomes. It seems as if drivers are more cautious driving at lower speeds and maintaining safe headways when driving on wet surface; such behavior has been suggested by past large-truck injury severity research (Chen and Chen, 2011; Duncan et al., 1998; Lemp et al., 2011; Zhu and Srinivasan, 2011a, 2011b).

Curved roadways were more risky for CDL drivers (parameter: +0.300, t-value: 4.88). Similar results were found in the literature for single-vehicle run off the road crashes (Gong and Fan, 2017a; Roque et al., 2015). Yet, a positive threshold parameter (+0.157) suggested that in the event of a crash, the outcome will likely be a possible injury but not an injury. This non-monotonic effect of road curvature suggest that in some cases, it seems that roadway curves are dangerous and can lead to severe outcomes while in few other cases, higher driver awareness and cautious driving, while maneuvering curved roadways, reduces the chances of injuries, in the event of crash (Lemp et al., 2011). Interactions of age groups with the curved roadways indicator revealed that older age drivers had the highest risk of injuries among other age groups.

Older vehicles were associated with higher severity levels across all age groups. The indicator variable for vehicles over 10 years of age was found to be heterogeneous around the mean of the estimated parameter with a t-value for its standard deviation of (+2.31). The severity of the driver's injury is likely associated with the vehicle's body and frame material composition. The automotive industry and manufacturers have been leaning towards utilizing light-weight materials in newer vehicles for benefits in fuel economy, drivability, and performance (Cole and Sherman, 1995). It is intuitive that in the event of a crash, a more solid-built vehicle (i.e. steel or cast iron) would have a heavier impacts relative to light-weight vehicles (i.e. aluminum and magnesium alloy) (Cole and Sherman, 1995; Miller et al., 2000).

CDL holders operating heavy-duty trucks were associated with lower injury propensities, yet the threshold specification suggested that in the event of a crash severe outcomes are expected across all age groups, with the young driver posing the least risk among other age groups. Young drivers are likely to have faster reaction time avoiding roadway obstacles. Interactions of other vehicle types and age groups indicated that older drivers in passenger-cars were associated with the lowest injury propensity among other age groups. Compared to larger vehicles, older drivers operating passenger-cars possess more commercial driving experience and likely to pay great attention to speed limits reducing the risk of severe single-vehicle crashes, especially in smaller vehicles.

A commercial driver operating a school bus was found to have a significant association with lower injury propensities (parameter: -0.588, t-value: -4.29). This result was intuitive and as expected for school bus drivers as they are typically well-trained and qualified to carry children to and from schools. School bus drivers are likely to be more cautious paying higher levels of attention to surroundings, street signs, and signals, operating at or below speed limits. A review of literature to-date has revealed a major deficiency in studies specifically analyzing school bus driver in the context of injury severity.

5.4. Temporal characteristics

Snowy conditions, compared to other weather conditions were associated with lower injury propensities across all age groups (parameter: -1.877, t-value: -3.43). Such results were also indicated through the positive threshold specification for the "snow" indicator (+0.634) in the event of a crash. The indicator variable for "snow" was found to be heterogeneous around the mean of the estimated parameter with a t-value for its standard deviation of (+3.53). Mid-age CDL drivers had the least risk compared other age groups driving in snowy conditions. With higher levels of training and precision of commercial drivers relative to standard driver license holders, CDL drivers are likely to be more cautious during adverse weather conditions, likely driving at slower speeds. The mid-age driver is more experienced than a younger driver with faster response to crash-developing situations, compared to older drivers. Similar results for snowy conditions were found in past studies for both single-vehicle and large truck crashes alike (Chen and Chen, 2011; Gong and Fan, 2017a; Lemp et al., 2011). Windy conditions slightly increased the injury propensity across all age groups. Crashes due wind do not necessarily involve impacting an object or a structure on the roadway.

Crashes occurring at nighttime, compared to daylight and dusk/dawn, increased the injury propensity across all age groups. Interactions of age groups with the "time-of-day" variable categories indicated that younger drivers were less risky during dusk/dawn conditions compared to other age groups.

Crashes on the weekdays were more severe compared to weekends across all age groups. Volumes of traffic on weekdays are likely higher compared to weekends representing more distractions and interactions crossing a segment of the roadway. Intuitively, if higher traffic volumes can lead to slower speeds; it can also lead to more distractions along the roadway. In the context of large truck crashes, Chang and Mannering (1999) found that weekend crashes increased the likelihood of a property-damageonly crash versus higher injury severity levels, however large trucks only account for a portion of CDL drivers (Chang and Mannering, 1999).

5.4. Measures of fit

To investigate the statistical significance of the MGORP model as compared to the standard ORP and its generalized version the GORP, likelihood ratio (LR) tests were conducted (McFadden, 1973). For more information regarding the LR test, readers are encouraged to refer to (Washington et al., 2003). In comparing two statistical models, the log-likelihood (LL) values at convergence for each unrestricted model (full model with all covariates) are compared to one another. Similarly, a LR test between an unrestricted model and its restricted version (same model with constants only and no covariates) is utilized to test the predictive power of each statistical model (ORP, GORP, and MGORP). The resulting test statistic is chi-square distributed, with degrees of freedom being equal to the difference in the numbers of parameters between the models being compared (Washington et al., 2003). Additionally, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) tests were conducted between the ORP, GORP, and the MGORP to test for model over-fitting. Tests such as AIC and BIC control for over-fitting in a model by introducing a penalty term in its calculation, which essentially grows with adding more parameters to the estimated model (Akaike, 1987; Schwarz, 1978). The model with the lowest AIC and BIC values is essentially the best-fit among all.

Table 4 summarizes the LR tests conducted between models as well as the AIC and the BIC statistics for the ORP, GORP, and MGORP models. Table 4 presents the LL values for the unrestricted and the restricted versions of each of the OPR, GOPR, and MGORP models. Additionally, Table 4 presents LR tests results between the ORP and the GORP, the GORP and the MGORP, and the ORP and the MGORP models. Table 4 also indicates all of the corresponding degrees of freedoms as well as the level of confidence (99.99% or more). Critical chi-squared values for each LR test conducted is shown in parenthesis next to the LR statistic value for each test.

It can be seen from the table of comparisons that the MGORP model is in fact superior to both the

TABLE 4 Measure-of-fit results and model comparisons

	ORP	**GORP**	**MGORP**
Number of Parameters	30	41	49
LL - Null Model	-4128.63	-4128.63	-4128.63
LL - Converged Model	-3814.47	-3720.37	-3684.02
LR (each model vs. its restricted version)	628.32 (56.892)*	816.52 (72.055)*	889.22 (82.720)*
LR ORP vs. GORP (df=11)	188.20 (31.264)*		
LR GORP vs. MGORP (df=8)	72.70 (26.124)*		
LR ORP vs. MGORP (df=19)	260.90 (43.82)*		
AIC	7688.94	7522.74	7466.04
BIC	7891.99	7800.24	7797.69

*Value in parenthesis is the critical chi-squared value for the corresponding model degrees of freedom at 99.99%

ORP and the GORP models based on LR tests and the AIC and BIC values. As the MGORP is considered a generalized version of the ORP model, both AIC and BIC values for the MGORP model of 7466.04 and 7797.69 respectively were the lowest values amongst all models which indicated a better fit of the MGORP to the dataset utilized in this study.

6. Elasticity Effects

The magnitude of the effects of the covariates on injury severity outcomes is not directly provided by the model's parameter estimates. In order to clearly quantify the impacts of these variables, some of which appear in both the risk propensity and the threshold functions for the MGORP model, it is necessary to compute their corresponding elasticity effects. Elasticity effects can be interpreted as the percent effect of a 1% change in a variable has on the severity outcome probability (Khorashadi et al., 2005). Elasticity calculations are not applicable to indicator variables; therefore an average direct pseudo-elasticity was calculated (Chen et al., 2015; Gong and Fan, 2017b; Islam et al., 2014; Islam and Brown, 2017; Li and Bai, 2008; Rusli et al., 2017b; Sarker et al., 2017; Washington et al., 2011; Wong et al., 2011; Wu et al., 2014; Yamamoto et al., 2008; Zhu and Srinivasan, 2011b). The pseudo-elasticity of a variable represents the average percent change in the probability of an outcome category when the value of that variable changes from 0 to 1. The elasticity results from the MGORP model are shown in Table 3.

6.1. Elasticity effects of MGORP model

In Table 5, elasticity effects were calculated for standalone variables across all injury severity outcomes. Cases where variables differed across age groups, elasticity effects were calculated for interaction terms but not the main variable as effects of main variables were already included in the effects of its corresponding interactions with the different age groups. Elasticity effects of the “main variable” (variable does not vary across age groups) are presented and interpreted horizontally in Table 5 across the different injury severity outcomes, while interaction effects are presented and interpreted vertically across age groups within each column corresponding to each injury severity level. For example, elasticity effects of the “female” variable, which is a “main variable”, indicate that females are 51.77% more likely to be possibly injured versus a reduction of that likelihood by 9.48% and 4.48% in the “injury” and “no injury” categories, respectively. Similarly, the value of 204.08 which corresponds to “seatbelt” not being utilized indicates that commercially-licensed drivers not using their seatbelt are 208.04% more likely to be injured in the event of a crash. The likelihood for “seatbelt” not being utilized was also increased in the “possible injury” severity outcome by 17.06% while reduced by 10.56% in the “no injury” category. For illustration purposes, curved roadways represent an example of a variable that varies across age groups. Elasticity effects indicate that, in the event of a crash, older drivers were 108.13% more likely to be injured, 56.41% more to be possibly injured, and a reduction of 11.07% of no injury (interpretation is captured horizontally in Table 5 across injury severity outcomes). In terms of interactions across age groups for curved roadways, the likelihood for injuries was increased by 108.13% for the “older” age group versus an increase of only 57.80% for both the “mid-age” and “younger” age groups alike. Since the “curved” indicator is found statistically significant as a standalone variable (before interactions), its effects were carried along for the “younger” and “mid-age” age groups, while additional effects of the “older” age interaction with “curve” produces the added risks imposed by older age drivers (additional effects for older drivers: 108.13% - 57.80% = 50.33%). Within each of the three columns of Table 5 (representing the three injury severity outcomes), elasticity effects of other interaction variables within any desired injury severity categories can be interpreted in a similar fashion.

TABLE 5 Elasticity effects of MGORP model across injury severity outcomes and age groups

		Elasticity (%)		
Explanatory Variables		**Injury**	**Possible Injury**	**No Injury**
Driver				
Gender (base: male)				
Female		-9.48	51.77	-4.48
Seatbelt Usage (base: used)				
Not used		204.08	17.06	-10.56
CDL origin state (base: in-state)				
Out-of-state		-24.90	-28.29	4.79
Accident				
Collision with (base: other)				
Animal		-91.22	-82.48	17.47
Fixed object		21.94	13.35	-2.69
Contributing factor (base: none, improper move, other)				
Speeding		98.77	30.06	-8.48
Distracted		-6.27	32.01	-2.63
Improper move	Young	0.00	0.00	0.00
	Mid-age	-13.78	-9.12	1.84
	Old	0.00	0.00	0.00
Freeway (base: not on freeway)				
On freeway		-98.95	-89.22	21.36
Roadway				
Number of lanes (base: multi-lane)				
Two-lane		-23.60	-15.63	3.69
Multi-lane	Young	0.00	0.00	0.00
	Mid-age	0.00	0.00	0.00
	Old	-30.95	-21.60	4.24
Roadway division (base: divided)				
Undivided		-	-	-
Undivided	Young	41.05	25.19	-3.91
	Mid-age	41.05	25.19	-3.91
	Old	93.82	52.33	-8.51
Speed limit (base: ≥ 55 mph)				
< 55 mph		-62.70	-47.08	12.06
Area type (base: rural)				
Urban		-36.76	-12.58	4.27
Surface condition (base: dry)				
Wet		-34.67	-35.32	7.02
Curvature (base: straight)				
Curved		-	-	-
Curved	Young	57.80	33.17	-6.20
	Mid-age	57.80	33.17	-6.20
	Old	108.13	56.41	-11.07
Vehicle age (base: < 5 years, 5-10 years)				
> 10 years		16.68	10.39	-1.96
Vehicle type (base: car, truck-light duty)				
Truck-heavy duty		-	-	-

TABLE 5 Continued

		Elasticity (%)		
Explanatory Variables		**Injury**	**Possible Injury**	**No Injury**
Truck-heavy duty	Young	-58.38	-43.96	9.72
	Mid-age	-34.94	-24.04	5.55
	Old	-34.94	-24.04	5.55
Car	Young	0.00	0.00	0.00
	Mid-age	0.00	0.00	0.00
	Old	-31.76	-22.20	4.35
School bus involved (base: not involved)				
Involved		-63.25	-49.62	9.43
Temporal				
Weather (base: clear, cloudy, rain)				
Snow		-	-	-
Snow	Young	-98.08	-95.06	18.44
	Mid-age	-83.72	-72.34	14.71
	Old	-98.08	-95.06	18.44
Wind		11.62	40.47	-4.83
Time-of-day (base: day, dusk/dawn)				
Night		8.29	5.19	-1.04
Dusk/dawn	Young	-65.57	-51.92	9.57
	Mid-age	0.00	0.00	0.00
	Old	0.00	0.00	0.00
Day-of-week (base: weekend)				
Weekday		11.19	7.05	-1.34

According to elasticity effects presented in Table 5, the most important variables that impose the highest risks of injuries across all age groups are seatbelt usage, speeding, roadway curvature, and roadway division. Variables effects that increase risks for the “possible injury” category are roadway curvature, roadway division, females, windy conditions, distracted driving, and speeding. Variables varying across age groups with the highest risks for older drivers sustaining possible injuries or injuries include curved and undivided roadways. Other variables also varying across age groups that decreased risks for a specific age group versus other age groups include snowy conditions, dusk/dawn, truck heavy-duty, passenger car, and multilane roadways.

6.2. Implications of variable effects and recommendations

Variable effects have important implications that can assist the FMCSA in fine-tuning current CDL standards, law enforcement, as well as shareholders and owners of businesses operating commercial vehicles. These implications can certainly benefit CDL drivers as well as other motorists sharing the roadway through the potential benefits of avoiding a crash or reducing the injury severity in the event of one. Implications can also be extended to training and education of commercially-licensed drivers.

In terms of CDL implications across all age groups, the modeling results and elasticity effects suggest periodic training and continuous enforcement of seatbelt usage. Law enforcement agencies should apply heftier fines on those who are drive without a seatbelt. Regulations that allow retesting of CDL holders, in the event that a citation regarding lack of seatbelt usage exists, are highly encouraged.

Speeding is generally considered a high risk factor that applies to both CDL and non-CDL holders alike. Most States have their own disciplinary system when a speeding violation occurs. For example, some States apply a point system that tracks dangerous or reckless drivers, while other States may simply take actions against holding the commercial license itself. These differences across the different States may function best if drivers are only allowed to drive within the boundary of the license's issuing state, yet this is not the case for most drivers. It is highly recommended that the FMCSA apply nationwide disciplinary rules along with additional disciplinary actions for individual States. Considering that CDL holders are generally drivers who obtain a higher level of knowledge, possess higher levels of skills and experience, higher fine rates and/or additional points should be applied to those who drive above speed limits.

Curved roadways presented higher risks for both "possible injury" and "injury" crashes when it comes to single-vehicle crashes, especially for the "older" age group. Additional driving tests on curved roadways should be mandated at the time of obtaining for a new commercial license. Additional training on curved roadways should be considered in the preparation of obtaining a CDL license. Furthermore, it is also suggested that specific lower speed limit signs added to curved segments of roadways that are based on the degree of the curvature and specifically aimed (specific speed limits) at commercial license holders.

Elasticity effects indicated that crashes on undivided roadways had higher risks for injuries, especially for the "older" age group. It would be beneficial if commercial traffic is routed to divided roadways through a specific routing mechanism. It is intuitive that some States may consider it extreme to nationally mandate the types of roadways utilized by commercially-licensed drivers, yet minimizing the usage of undivided routes may reduce the likelihood of the occurrence of a single-vehicle crash.

It is highly unlikely to believe that the set of skills, experiences, and the trainings received during the process of obtaining a CDL license will differ among males and females, yet due to the physiological gender differences, and in the event of a crash, female drivers are more susceptible to higher injury severity levels. The MGORP elasticity results for females are intuitive and suggest that commercially-licensed female drivers should learn more about the factors that specifically increase the risks of single-vehicle crash occurrence and be more cautious when traveling on the road.

Driving through windy conditions contributed to a higher likelihood of a "possible injury" crash. CDL drivers should be required to attain specific training on the potential weather conditions that can lead to higher risks of injury crashes. It is suggested that drivers reduce their speeds in windy conditions or avoid driving when specific wind speeds are forecasted.

CDL holder should be more cautious and avoid distracted driving at all times. Law enforcement should apply additional fines to those who are not found in compliance. Rules such as those mandated effectively on October 27, 2010, by the FMCSA which was published to limit the use of wireless communication devices while operating on interstate commerce (The Federal Motor Carrier Safety Administration (FMCSA), 2010). Such policies should be enforced to the highest levels.

7. Conclusions

Past research that focused on specifically the injury severity of commercially-licensed drivers is almost non-existent. Particularly, commercially-licensed drivers involved in single vehicle crashes are underrepresented in the injury severity literature. Factors contributing to the severity of single-vehicle crashes involving CDL holder are most certainly different in nature due to the higher level of knowledge, experience, skills, and physical abilities compared to the holders of a standard driver's license. Different age groups behave differently while on-the-road due to certain physical abilities, years of experience, and physiological differences. This research effort aims to fill this gap in the literature by undertaking an extensive empirical analysis of single-vehicle crashes involving commercially-licensed drivers by using four years of crash databases in the State of Minnesota. The authors investigated the factors affecting the injury severity level of CDL holders. The empirical analysis employed the mixed generalized ordered response probit (MGORP) model that recognized the ordinal nature of the severity outcomes while allowing for heterogeneity to capture the effects of unobserved factors. The primary focus of this study is to uncover the potential interaction effects that the different age groups impose on the factors contributing to a single-vehicle crash. To the authors' knowledge, this is the first study to explore such factors affecting the injury severity of commercially-licensed drivers involved in single-vehicle crashes while investigating the moderating effects of the drivers' age groups on the covariates considered in the study.

The MGORP model that accounts for unobserved heterogeneity and threshold heterogeneity across crashes was found to fit the data better compared to the fixed parameters ORP model. The MGORP model elasticity effects indicates that key factors that increase the likelihood of severe crashes for commercially-licensed drivers across all age groups include: lack of seatbelt usage, speeding, curved roadways, undivided roadways, collision with a fixed object, vehicle age of 11 or more years, wind, weekdays, night time, and females. With regards to variations across the different age groups, significant differences were observed in the effects of the following factors – improper move, multi-lane highways, undivided roadways, curved roadways, passenger car, heavy-duty trucks, snow, and dusk/dawn. In terms of the limitations of this study, there were very few variables in the database describing different types driver actions or maneuvers prior to crash occurrence (for example, traveling straight, making a right or left turn, backing, parking, etc.). Future scope of research may include the collection of a comprehensive multi-state dataset could be beneficial to test spatial transferability of the model developed in this study. Future research may also include the specific testing requirements and the type or class of the CDL license being obtained can be investigated to gain further insights on the factors contributing the each license's class. Also, a non-behavioral comparison between CDL and non-CDL drivers in the context of injury severity analysis can be considered a future research to be explored. Due to the as-is complexity of interaction terms, their interpretation, and elasticities to be introduced within one research study, another venue for future work can include the moderating effects (interactions) of other factors, such as gender, on the injury severity of single-vehicle crashes involving CDL holders.

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