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ANALYSIS OF FACTORS INFLUENCING THE VEHICLE DAMAGE LEVEL IN FATAL TRUCK-RELATED ACCIDENTS AND DIFFERENCES IN RURAL AND URBAN AREAS

ABSTRACT

Accidents involving large trucks very often end up with deadly consequences. Innocent people getting killed are acknowledged globally as one of the traffic safety greatest problems and challenges. While risk factors on truck-related accidents have been researched extensively, the impact on fatalities has received little or no attention, especially considering rural and urban areas, respectively. In this study, the generalized ordered logit model was used in Stata 11.0 to explore the complex mechanism of truck-related accidents in different areas. Data were obtained from The Trucks in Fatal Accidents database (TIFA). The Akaike Information Criterion (AIC) indicates that the model used in this paper is superior to traditional ordered logit model. The results showed that 9 variables affect the vehicle damage level in a fatal crash in both areas but with different directions. Furthermore, 23 indicators significantly affect the disabling damage in the same manner. Also, there are factors that are significant solely in one area and not in the other: 12 in rural and 2 in urban areas.

KEY WORDS

fatal truck-related accident; generalized ordered logit model; risk factors; marginal effect; traffic safety;

1. INTRODUCTION

In 2012, there were 3,921 people killed in crashes involving large trucks (gross vehicle weight rating greater than 4,536 kilogram) in the United States. Fatalities in crashes involving large trucks showed 4% increase from 3,781 in 2011 to 3,921 in 2012. These large trucks accounted for 8% of fatal crashes but large trucks only accounted for 4% of all registered vehicles [1]. Obviously, truck-related crashes lead to substantial economic and emotional losses to the society, so how to improve truck drivers' safety has become not only a safety issue but also essential to raise the happiness index and the economic development of the nation.

Considerable research efforts had been spared to investigate risk factors of truck-related accidents. In reviewing previous studies of injury severity in accidents involving trucks, it was easy to find that, up to date, there were limited studies focusing on how to alleviate fatal truck accidents. It can be summarized that identifying and gaining a comprehensive understanding of the factors that contribute to the fatal truck-related crash is significantly meaningful. Also, from previous studies it was found that fatal crashes in rural and urban areas had different mechanisms of occurrence. The effects on resulting injury severities in two areas were very different which is a crucial fact in implementing more effective and efficient injury prevention strategies to enhance safety [2, 3].

Considering these arguments, there exists, however, a gap between the current studies and the reality in ignoring the possibility to investigate how to alleviate fatal truck-related crashes and ignoring the unique properties of traffic environments in rural and urban areas. To narrow such a gap, this study considers fatal truck-related accidents in rural area and urban area separately. In order to analyze the risk factors on fatal truck-related accidents, the extent of damage is introduced as an ordered dependent variable with values including no damage, minor damage, functional damage and disabling damage. It reflects the vehicle damage level of the fatal truck-related accidents. No damage means the truck is no operation problem. Minor damage means that accident does not affect the operation of the truck. Functional damage means not disabling, but affects the operation of the truck or its parts. Disabling damage means that the vehicle needs repair to be able to operate normally.

Furthermore, in order to overcome the restrictions of the traditional ordered logit model, a generalized ordered logit model is used. With this model the relationship between the extent of damage and the driver characteristics, vehicle characteristics, roadway characteristics and environmental conditions is explored.

2. METHODOLOGY

The ordinal or ordered logistic regression presents a tool for the analysis of situations when the outcome for a dependent or response variable (the output) has at least three ordered possibilities. Like other forms of regression analysis, logistic regression makes use of independent or input variables (the explanatory variables) that are in our case categorical. These are put together in a design matrix denoted *X*, which is a matrix of explanatory variables. The response variable vehicle damage level is inherently ordinal discrete, so a categorical response model is used to identify the factors affecting it. Commonly, statistical formulation to model vehicle damage level is the ordered response formulation, especially ordered logit model or ordered probit model [4, 5, 6, 7, 8, 9, 10, 11, 12, 13]. The main difference between the two ordered models is the assumption of distribution of the error term. The former model assumes a logistic distribution and the latter model assumes a normal distribution. Actually, the results of the two models are very similar. The model's structure includes the associated latent variable

$$Y^{*}=\alpha+X'\beta+\varepsilon \tag{1}$$

measuring the vehicle damage level. *X* is a vector of independent variables (*X'* is a transpose of *X*), α is the intercept parameter, β is the vector of parameters which are also supposed to be estimated and ε is the logit distribution error term. Unlike the observed data denoted *Y* and *X*, the latent variable is unobservable. A regression model tries to relate or find a link between the response variable Y on one side and *X*, α and β on the other side: $Y \sim f(X,\alpha,\beta)$. Furthermore, unlike the ordinary regression, the parameters contained in α and β cannot be expressed by an exact formula of *Y* and *X* values. Instead, they are found by an iterative procedure from the statistical software. The probability of a dependent variable for each crash i is:

$$P(Y_i > j) = \frac{e^{\alpha_j + x_i'\beta}}{1 + e^{\alpha_j + x_i'\beta}}, \quad j = 1, 2, \ldots, M-1 \tag{2}$$

where *M* is the number of categories of the dependent variable, X_i is a vector containing the values from the full set of independent variables, α_j are called cutpoints [14, 15].

However, there is a key problem with the ordered logit model. Its assumption is often violated because they impose the restriction that regression parameters are constant across vehicle damage level, called parallel-lines assumption. In reality, however, it is not clear whether distances between adjacent injury levels are equal [15, 16, 17]. To solve this problem, some researchers have employed the unordered response model allowing the impact of independent variables to vary across different levels. This type of models were widely used to analyze traffic safety problems including multinomial logit models, nested logit model, mixed logit models and etc. [11, 17, 18, 19, 20, 21, 22]. Many other researchers also introduced a generalized ordered logit model (*gologit*), which is less restrictive and more parsimonious and interpretable [16, 23, 24]. In this paper, *gologi*t is used to analyze the truck-related fatal accidents.

Gologit2 [15] is a user-written program in statistical package *Stata* which, among other things, measures contrasts between categories. Program output is given in panels e.g. the first panel contrasts category 1 with categories 2, 3, and 4; the second panel contrasts categories 1 and 2 with categories 3 and 4; and the third panel contrasts categories 1, 2, and 3 with category 4. Positive coefficients indicate that higher values on the explanatory variables make it more likely that the response will be in a higher category of *Y* than the current one, whereas negative coefficients indicate that higher values on the explanatory variable increase the likelihood of being in the current or a lower category.

This model, compared to *Equation 2*, can be written as:

$$P(Y_i > j) = \frac{e^{\alpha_j + X_i'\beta_j}}{1 + e^{\alpha_j + X_i'\beta_j}}, \quad j = 1, 2, \ldots, M-1 \tag{3}$$

where *M* is the number of categories of the dependent variable. If the logistic function is introduced, $g(x) = \frac{e^x}{1+e^x} = \frac{1}{1+e^{-x}}$, the probability of *Y* can be expressed as:

$$P(Y_i = 1) = 1 - g(\alpha_1 + X_i'\beta_1) \tag{4}$$

$$P(Y_i = j) = g(\alpha_{j-1} + X_i'\beta_{j-1}) - g(\alpha_j + X_i'\beta_j), \quad j = 2, \ldots, M-1 \tag{5}$$

$$P(Y_i = M) = g(\alpha_{M-1} + X_i'\beta_{M-1}) \tag{6}$$

Formulas 2 and *3* for ordered logit and *gologit* are almost the same, except for parameter β, which is the same for all values of *j* in ordered logit, but the *gologit* model allows β to differ for each of the M-1 values. Special attention must be paid to the interpretation of coefficients of the intermediate categories, because it is not clear what effect a positive or negative β has on the probability of those "interior" categories [25]. To overcome this difficulty, marginal effects are computed and used to interpret the variables. The marginal effect measures the impact of change in the independent variables on the expected change in the dependent variable in a regression model, especially when the change in the independent variable is infinitely small or merely marginal [26]. For a dummy variable, a marginal effect is calculated as follows:

$$Mar_{x_{jnk}}^{P(Y_i>j)} = P(Y_i > j \mid x_{jnk} = 1) - P(Y_i > j \mid x_{jnk} = 0) \tag{7}$$

where x_{jnk} is the *k*-th independent variable of individual *n* on vehicle damage level *j*. $\rho^2=1-LL(\beta)/LL(0)$ and

Akaike's information criterion (AIC=-2ln$LL(\beta)$+2p) are applied to measure the overall model fit. In the formulas $LL(\beta)$ is the log likelihood at convergence with parameters β and $LL(0)$ is the log likelihood with only the intercept coefficient, p is the total number of parameters. ρ^2 has the same meaning as R^2 in regression models [25]. *AIC* reflects the goodness of fit of the model compared to some other models and smaller *AIC* indicates well performance of the model [27].

3. DATA PREPARATION AND OVERVIEW

Data in our empirical study are from the Trucks in Fatal Accidents (TIFA) 2010 dataset and can be downloaded from the National Highway Traffic Safety Administration (NHTSA) – U.S. Department of Transportation official website. The 2010 TIFA file contains records for all large trucks that were involved in fatal accidents in the 50 states and the District of Columbia during calendar year 2010. All the vehicles described are from Version 3, February 12 of the Fatality Analysis Reporting System (FARS) file for 2010 accidents, developed by the NHTSA. The TIFA file contains five main variables: the crash variables, the vehicle variables, the driver variables, the occupant variables and the survey variables. For the purpose of this study only part of the variables were extracted from the files, namely, driver characteristics including driver drinking, prior to recognition of critical event and attempted avoidance manoeuvre, vehicle characteristics including vehicle number, weight, and manner of collision, roadway characteristics including specific location, total lanes, alignment, grade, work zone, control device, traffic way description and environmental conditions including atmosphere, light, period, speed limit.

The dataset contains 3,699 fatal cases resulting in 4,154 fatalities and each crash involves at least one fatality. The study is focused on factors contributing to fatal truck-related accident so extent of the vehicle damage is considered as a dependent variable. A four point ordinal scale is used to describe the extent of the damage of the vehicle in an accident: (1) No damage, (2) Minor damage, (3) Functional damage, (4) Disabling damage. Also, in the dataset there are 6 individuals not reported and 41 individuals unknown that are excluded from the analysis (about 1.27% of the sample). In order to compare the differences between urban and rural areas 19 unknown individuals (about 0.51% of the sample) were also excluded. As a result, 3,633 cases of fatal accidents in the final dataset are valid to be used and the distribution of vehicle damage level is: No damage 5.09%, Minor damage 17.34%, Functional damage 17.29% and Disabling damage 60.28%. 66.31% fatal accidents occur in rural areas, 33.69% occur in urban areas. The detailed vehicle damage percentage distribution of the data is shown in *Table 1*.

The dataset is chosen in such a way as to restrict the set of all accidents and focus on a subset with available information. Although only fatal truck-related accidents are observed, the point is to emphasize the factors and differences in their influence between the rural and urban areas. One must be aware that there will be typically more fatal truck-related accidents with minor vehicle damage in urban areas than in the rural ones, since most of the truck-hit-pedestrian accidents happen in the urban area. Also, high-speed accidents are more likely to occur in rural area because bigger sections of the roadway system are highways there, so the damage is higher. This, however, does not have an effect in our methodology.

4. RESULTS OF THE ANALYSIS AND THEIR INTERPRETATION

The generalized ordered logit models are developed for rural area and urban area separately. Each model predicts four levels of extent of damage: No damage, Minor damage, Functional damage and Disabling damage. Generalized ordered logit models are fitted by a user-written program *gologit2* in *Stata 11.0* [15]. During model estimation a two-tailed z-test is used to determine if the coefficients are significant at level 0.05. In order to measure the effects of the independent variables, marginal effect of individual factors on the extent of damage is further explored as presented in *Table 2*. Notably, in marginal effect, variables are reserved with at least one estimate significant at the 0.05 level, since they are associated with the independent variable [28].

In summary, as shown later in *Figure 1*, there are 9 contributing factors that significantly affect the disabling damage in both areas but with different directions of influence. Also it can be seen in *Figure 2* that there are 23 indicators significantly affecting the disabling damage in the same direction (increase or decrease) in both areas.

Ordered logit models are also introduced and compared with the generalized ordered logit models and the latter have better performance. So, the detailed results of ordered logit models are not given. Parameters

Table 1 – Detailed vehicle damage percentage distribution.

Area	No damage	Minor damage	Functional damage	Disabling damage	Total
Rural	2.31%	8.65%	10.91%	44.45%	66.31%
Urban	2.78%	8.70%	6.39%	15.83%	33.69%
Total	5.09%	17.34%	17.29%	60.28%	100.00%

Table 2 – Marginal effect of rural area and urban area.

Variables	Dummy variables	Rural area				Urban area			
		No	Minor	Functional	Disabling	No	Minor	Functional	Disabling
Vehicle number (base: single vehicle)	Multiple vehicles	0.010	0.074	0.060	-0.134	-	-	-	-
	Two vehicles	0.001	0.013	0.014	-0.027	-	-	-	-
Specific location (base: non-junction)	Intersection	-	-	-	-	-	-	-	-
	Intersec-tion-related	0.006	0.116	0.131	-0.047	-0.002	0.120	-0.063	-0.055
	Driveway	0.001	0.039	0.190	-0.229	-0.002	0.026	0.145	-0.168
Total lanes in road-way (base: one lane)	Four lanes	-0.004	0.231	-0.343	0.112	-	-	-	-
	Three lanes	-	-	-	-	-	-	-	-
	Two lanes	-	-	-	-	0.055	-0.003	0.002	-0.054
Alignment (base: straight)	Curve	-0.004	-0.067	-0.023	0.090	0.018	-0.190	0.218	-0.046
Light condition (base: daylight)	Dark - not lighted	-0.001	-0.003	-0.013	0.016	-0.003	0.090	-0.065	-0.022
	Dark - lighted	0.104	-0.031	-0.073	0.003	-	-	-	-
Atmosphere condi-tion (base: clear)	Rain	0.010	0.015	0.034	-0.049	-0.019	-0.008	0.154	-0.127
	Sleet	-	-	-	-	-	-	-	-
	Snow	0.047	-0.017	0.022	-0.006	0.102	0.088	-0.254	0.064
	Fog	-	-	-	-	-	-	-	-
	Cloudy	-0.001	-0.024	0.043	-0.019	-	-	-	-
Work zone (base: no)	Yes	-0.005	0.049	0.125	-0.076	0.000	-0.132	0.071	0.062
Period (base: weekday)	Weekend	-0.001	-0.028	-0.012	0.040	0.014	0.101	-0.005	0.092
Weight (base: light)	Heavy	0.005	0.023	-0.013	-0.010	-0.003	0.115	-0.049	-0.063
Control device (base: no)	Yes	0.003	0.064	-0.032	-0.032	0.000	0.038	0.037	-0.076
Driver drinking (base: yes)	No	0.002	0.041	0.110	-0.151	0.003	0.158	0.051	-0.212
Traffic way descrip-tion (base: one way)	Two-way, not divided	-0.001	0.031	-0.075	0.044	0.004	0.086	-0.106	0.017
	Two-way, divided with median	-0.003	0.071	-0.088	0.017	0.091	-0.033	-0.064	0.006
	Two-way, with left-turn lane	-0.001	-0.076	0.055	0.020	-0.004	-0.051	0.103	-0.049
Manner of collision (base: no collision)	Front-to-rear	-0.003	-0.019	0.097	-0.079	-0.034	-0.286	0.202	0.118
	Front-to-front	-0.091	-0.106	-0.133	0.240	-0.020	-0.353	0.018	0.355
	Angle	-0.008	-0.052	0.031	0.022	-0.037	-0.302	0.106	0.233
	Sideswipe - same direction	-0.003	0.037	0.055	-0.092	-	-	-	-
	Sideswipe - opposite direction	0.011	0.185	0.022	-0.207	-	-	-	-
	No driver present	0.017	-0.033	0.127	-0.094	-0.010	0.166	0.024	-0.180

Variables	Dummy variables	Rural area				Urban area			
		No	Minor	Functional	Disabling	No	Minor	Functional	Disabling
Prior to recognition of critical event (base: go straight)	Decelerating in traffic lane	0.005	0.075	-0.065	-0.010	0.008	0.155	-0.063	-0.100
	Accelerating in traffic lane	0.092	0.296	0.245	-0.542	-	-	-	-
	Starting in traffic lane	-0.003	0.334	-0.070	-0.265	-0.005	0.218	-0.026	-0.187
	Stopped in traffic lane	-0.003	0.138	0.141	-0.279	0.024	0.251	0.011	-0.286
	Passing or overtaking a vehicle	-	-	-	-	-	-	-	-
	Turning right	-	-	-	-	0.035	0.190	0.223	-0.448
	Turning left	0.010	0.210	0.197	-0.408	0.061	0.183	-0.383	0.139
	Negotiating a curve	-0.004	-0.078	-0.073	0.151	-	-	-	-
	Changing lane	-0.003	0.045	0.171	-0.216	-0.012	0.329	-0.205	-0.112
Attempted avoidance manoeuvre (base: no)	Braking	-0.016	-0.040	-0.018	0.058	-0.011	-0.125	0.194	-0.058
	Steering	0.002	-0.061	-0.009	0.070	-0.013	-0.087	0.096	0.004
	Braking and steering	-0.003	-0.035	-0.060	0.094	-	-	-	-
Speed limit (base: under 13.411m/s)	15.646m/s								
	17.881m/s								
	20.117m/s	-0.003	-0.045	-0.113	0.158	-0.019	-0.170	0.065	0.124
	22.352m/s	-	-	-	-	-	-	-	-
	24.587m/	-0.009	-0.079	-0.098	0.177	-0.023	-0.182	0.095	0.110
	26.822m/s	-0.003	-0.053	-0.011	0.064	-0.019	-0.002	0.122	-0.102
	29.058m/s	-0.006	-0.090	-0.083	0.172	-0.030	-0.204	0.118	0.116
	31.293m/s	-0.004	-0.069	-0.018	0.088	-0.016	-0.200	0.164	0.052
	Over 33.528m/s	-0.004	-0.075	-0.069	0.145	0.000	0.000	-0.462	0.462
Roadway grade (base: level)	Hillcrest	0.024	-0.159	-0.010	0.169	-	-	-	-
	Uphill	0.001	0.036	-0.071	0.035	-	-	-	-
	Downhill	0.005	-0.124	-0.016	0.140	0.061	-0.093	-0.156	0.187

Notes: - not significant.
Source: gologit2 + Stata 11.0

to evaluate the accuracy of the models are shown in *Table 3*. From the AIC (rural: 4,124.819 vs. 4,194.705; urban: 2,767.470 vs. 2,786.128) and Pseudo R^2 (rural: 0.175 vs. 0.103; urban: 0.206 vs. 0.115) the generalized ordered logit regression model has superior performance.

Figures 1 and *2* give a graphical presentation of similarities and differences between rural and urban areas. In the following subsections the positive and negative influence of the independent variables used in the models are discussed in detail from driver characteristics, vehicle characteristics, roadway characteristics, and environmental conditions, respectively.

Table 3 – Comparison of traditional logit model and generalized logit model

	Log likelihood	Pseudo R^2	AIC
	Rural area	Number of observations	2,409
Ordered logistic regression	-2,032.352	0.103	4,194.705
Generalized Ordered Logit regression	-1,869.400	0.175	4,124.819
	Urban area	Number of observations	1,224
Ordered logistic regression	-1,328.064	0.115	2,786.128
Generalized Ordered Logit regression	-1,190.735	0.206	2,767.470

Source: Stata 11.0

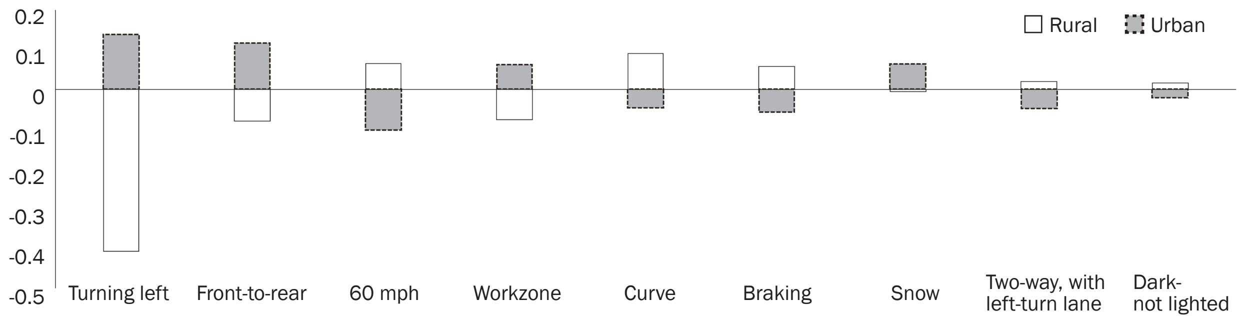

Figure 1 – Comparison of nine variables affecting disabling damage in both areas but with different directions

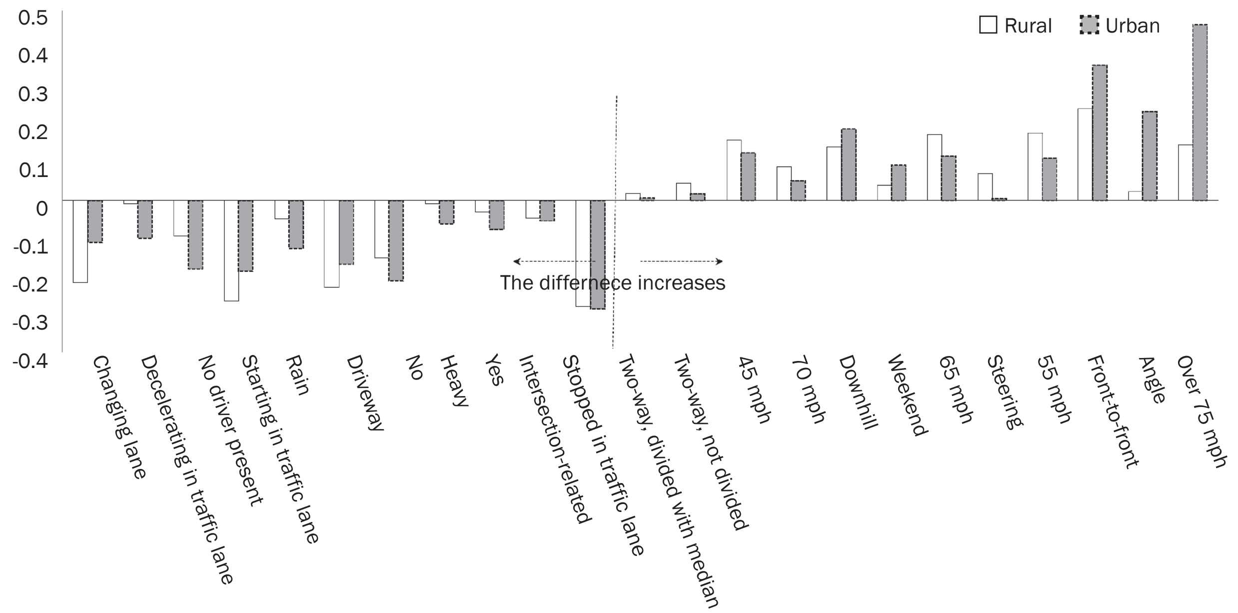

Figure 2 – Comparison of 23 variables affecting disabling damage in both areas with same directions

4.1 Driver characteristics

The impact of driver characteristics on vehicle damage level in a fatal crash becomes significant when considering drinking, no driver present, decelerating in traffic lane, accelerating in traffic lane, starting in traffic lane, stopped in traffic lane, turning left, negotiating a curve, braking, steering, braking and steering in rural area. Difference is observed in the urban area where accelerating in traffic lane and negotiating a curve are not significant, but turning right is.

Different effects on the vehicle damage level are obtained from the driver drinking. In the data sample, about 3.24% of the truck drivers in rural area and 2.21% in urban area drink before accidents, which seemed to be low. However, in those samples the proportion of disabling damage is high (rural: 84.88% and urban: 66.67%). It is true that no drinking could decrease the probability of disabling damage (rural: -0.151 and urban: -0.212) and increase the probability of the other three vehicle damage levels, because marginal effects of them are greater than 0. This result is expected and it is the same as the relationship found between drinking and crash severity in [29, 30, 31, 32].

Considering the prior to recognition critical event, not all of the events significantly affect the vehicle damage level and the significant types of events differ between rural area and urban area. Passing or overtaking a vehicle has no significant effect on both rural and urban area. Accelerating in traffic lane is significant in rural area and decreases the likelihood of the disabling damage (-0.542) but is not significant in urban area. Compared with the urban area, in rural area negotiating a curve is more likely to be significantly associated with disabling damage (0.151), functional damage (0.073), minor damage (-0.078) and no damage (-0.004). Possibly, in urban areas the roadway curve is less complicated than in the rural area because from the samples 80.71% of disabling damage results from negotiating a curve in rural area but only 66.39% in urban area. On the contrary, it is found that turning right decreases the chance of disabling damage (-0.448) in urban but is not significant in rural area.

Although different significance in prior to recognition critical event between the rural area and urban area is observed, some variables have significant influence on vehicle damage level in both areas. For example, when collision involves a truck without driver, it is more prone to alleviate the crash disabling damage (rural: -0.094, urban: -0.180) but aggravate the functional damage (rural: 0.127, urban: 0.023). Decelerating in traffic lane, which has the same effect on all crash damage levels in two areas, can alleviate the vehicle damage level as well as starting and stopping in the traffic lane. Changing lane, which has a positive effect to avoid the disabling damage by -0.216 in rural, -0.112 in urban area, also decreases the probability of no damage (rural: -0.003, urban: -0.012) and functional damage in urban -0.021, but it increases the likelihood of minor damage (rural: 0.045, urban: 0.329) and functional damage in rural by 0.171. Interestingly, changing lane decreases the probability of both the high and low extent of damage but increases the median extent of damage.

Braking has a negative effect on vehicle damage level in rural area. In comparison with disabling damage, there is a decrease in the likelihood of no damage by -0.016, of minor damage by -0.040, of functional damage by -0.018. In urban area, braking increases the probability of functional damage by 0.194, but decreases the probability of no damage by -0.011, minor damage by -0.125 and disabling damage by -0.058. Steering in general also has a negative effect on vehicle damage level in both areas. It increases the probability of disabling damage (rural: 0.070, urban: 0.004) and functional damage (urban: 0.096) but has an opposite effect with a decrease in the probability of minor damage (rural: -0.061, urban: -0.087) and no damage by -0.013 in urban. Braking and steering is only significant in rural area. It is also associated with increasing casualties, as the probability of disabling damage rises by 0.094.

4.2 Vehicle characteristics

Crashes involving multiple trucks and two vehicles are found to be less severe in rural area, with a negative probability for disabling damage: -0.134 for multiple vehicles and -0.027 for two vehicles. This result is similar to the conclusion of [3, 33, 34, 35]. On the contrary, multiple trucks and two vehicles increase the likelihood of no damage by 0.010 and 0.001, minor damage by 0.074 and 0.013, functional damage by 0.060 and 0.014, respectively. The difference between truck weight in terms of vehicle damage level is statistically significant for a slightly lower probability to disabling damage (rural: -0.010, urban: -0.063) and functional damage (rural: -0.013, urban: -0.049). Obvious conclusion that light truck is prone to increase the probability of more severe crash is also found by [33, 36, 37].

Manner of collision is found significantly related to vehicle damage level in rural area for all types but in urban only for front-to-rear, front-to-front and angle type of collision. Many variables of manner of collision show similar effects in both rural and urban areas. For front-to-front collision, an increase in the probability of disabling damage is observed (rural: 0.240, urban: 0.018) and a reduction in the probability of no damage (rural: -0.091, urban: -0.020), minor damage (rural: -0.106, urban: -0.353). The influences of angles on vehicle damage level differ greatly in magnitudes for rural and urban area: increasing probability of disabling damage by 0.022 in rural area and 0.233 in urban area, of functional damage by 0.031 in rural area and 0.106 in urban area. On the other side, the probability of minor damage and no damage changes toward different direction in the decrease by -0.052 and -0.008 in rural area as well as -0.302 and -0.037 in urban area, respectively. Except for those indicators that have similar effect in both areas, front-to-rear presents substantial differences between the two areas whose impacts on disabling damage are opposite (-0.077 vs. 0.118). It is worth mentioning that the sideswipe-same and sideswipe-opposite directions are only significant in rural area in a general trend to alleviate the vehicle damage level.

4.3 Roadway characteristics

Regarding roadway characteristics, large disparities are found between the rural and urban areas. Although work zone indicator and alignment indicator are found significant in both areas, their effects on vehicle damage level are opposite. In rural area, a work zone decreases the probability of disabling damage by -0.076 but increases the probability of functional damage by 0.1251. For urban area, however, a work zone increases disabling damage by 0.062. Such findings suggest that there may exist complex interactions between vehicle damage level and work zone. The alignment indicator increases disabling damage by 0.090 and decreases no damage by -0.023 in rural area. On the contrary, it decreases the probability of disabling damage (-0.046) and increases the probability of no damage (0.018). Maybe the alignment in rural area is much more complex than in urban area and drivers fail to adjust their speed to curves [38]. The occurrence of a truck-related accident in an intersection-related in comparison with a non-junction roadway section slightly reduces the probability of disabling damage (rural: -0.047, urban: -0.055) and increases the probability of minor damage (rural: 0.116, urban: 0.120). This result agrees with the conclusion of [28] for bus accidents.

Some variables are found to have the similar effect between rural area and urban area. Driveway reduces the likelihood of disabling damage (rural: -0.229, urban: -0.168) but increases the likelihood of functional damage (rural: 0.190, urban: 0.145). Maybe the driveway speed is low which alleviates vehicle damage level, but it is also dangerous and slight damage is still likely to happen. Control device also reduces the probability of disabling damage by -0.032 in rural and -0.076 in urban are, but increases the probability by 0.064 in rural and 0.038 in urban area.

Compared to one-way road, two-way either with median or without median aggravates the vehicle damage level, but with a median it is safer in rural (0.017 vs. 0.044) and in urban area (0.006 vs. 0.017). Such a finding echoes those of previous studies and highlights the importance of providing more physical protection for drivers [39, 40].

Other variables are significant only in one area. For instance, road with four lanes is only significant in rural area and increases the probability of disabling damage by 0.112 but it strongly decreases the probability of functional damage by -0.343. In urban area there are a few roadways with four lanes but many with two lanes. In this situation the likelihood of disabling damage is reduced by -0.054. Uphill, downhill and hillcrest are all significant in rural area and increase the probability of disabling damage by 0.035, 0.140 and 0.169, respectively. Some others also found that truck crashes occurring downhill are more severe [41, 42]. In urban areas downhill is also significant in increasing the likelihood of disabling damage.

4.4 Environmental conditions

When a crash occurs on a weekend, it is by 0.040 and 0.092 more likely to result in disabling damage for rural area and urban area, respectively. Compared to daylight, serious crash is prone to happen in the dark. However, in rural area, the dark-lighted road is safer than the dark not-lighted road (increases the probability of disabling damage by 0.003 vs. 0.016) which was also found in the study of [29]. This finding highlights the importance of lighting on rural roads which may be considered in the future mitigation efforts at some crash hot spots [40].

According to the marginal effect table, rain, snow and cloudy conditions reduce the probability of disabling damage by -0.049, -0.006 and -0.019 in rural area, respectively. This finding is consistent with several previous studies [39, 40, 43]. Ma et al. pointed out that such an effect could be partly explained by the fact that the driver tends to drive more cautiously during the inclement atmosphere condition [40]. Meanwhile, in urban area, rain has the same effect as in rural area. However, snow increases the probability of disabling damage in urban area.

High speed limit is associated with aggravating truck-related accident vehicle damage level. In comparison with speed limit under 13.411 m/s over 33.528 m/s significantly increases the probability of disabling damage by nearly 0.146 in rural area and 0.446 in urban area.

5. CONCLUSION AND DISCUSSION

In the current study, a generalized ordered logit model is used to investigate and analyze the underlying risk factors of fatal truck-related accidents in rural area and urban area in the United States. Compared with the ordered logit model, this model accounts for the ordered nature of levels of crash damage as well as overcomes the violation of the proportional odds assumption across levels. The risk factors include driver characteristics, vehicle characteristics, roadway characteristics and environmental conditions. A dataset for analysis is retrieved from the TIFA, which is a census of all large trucks in fatal accidents in the United States during 2010. Model results allow the evaluation of the statistical significance of the various risk factors and the impact on vehicle damage level of fatal truck crash.

As shown in *Table 2* and *Figure 1*, there are nine contributing factors that significantly affect disabling damage in both areas but with different directions of influence: curve, dark - not lighted, snow, work zone, two-way with left-turn lane, front-to-rear, turning left, braking and speed limit 26.822 m/s. Notably, when doing roadway improvements, one should consider those indicators to reduce the likelihood of disabling damage in the two areas, respectively. Furthermore, in *Figure 2* there are 23 indicators significantly affecting the disabling damage in the same direction (increase or decrease) in both areas. From those, 11 factors which reduce the probability of disabling damage alleviate to some extent the severity of the crash, while other 12 factors have the opposite effect.

Other variables are found to be significant in either the rural area or the urban area, but not both. There are 12 important contributing factors that are only significant in rural area: multiple vehicles, two vehicles, four lanes, dark-lighted, cloudy, sideswipe-same direction, sideswipe-opposite direction, accelerating in traffic lane, negotiating a curve, braking and steering, hillcrest, uphill. Comparatively, there are only two important contributing factors significant in urban areas only: two lanes and turning right.

Development of models to analyze the vehicle damage level of medium and heavy trucks in fatal accidents in rural and urban areas is helpful in identifying and understanding complex interactions between specific critical factors and accidents in different regions. Although this study focused on the vehicle damage it did obtain the information which can provide governments or truck companies with some reference to improve traffic safety. It reflects the vehicle damage level of the accidents. We managed to pinpoint the factors influencing the vehicle damage level and, furthermore, to find differences between the rural and urban areas. There are, however, some limitations in the current study to be improved in the future, such as driver demographics (age, gender) which are not included in the model due to the incompleteness of the dataset. The interaction effects of multiple variables are not considered in the models. In the future study, it is recommended that more expansive database should be built to validate the models. Also establishing pre-crash model may be more interesting and more efficient to reduce the number of accidents.

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城市与乡村卡车死亡事故中车辆损坏程度的影响因素对比分析

摘要
大型卡车容易发生交通事故，并且后果严重，对人们的生命安全和财产带来了极大的威胁，其已经成为研究的一大难题和挑战。虽然目前关于卡车事故，已经进行了相关的研究，但是针对卡车死亡事故，将乡村和城市分开进行的研究较少。本研究中，基于卡车死亡数据库中的数据，利用广义有序logit模型对不同区域卡车事故机制进行了分析。AIC结果表明，本文的模型优于传统的有序logit模型，所有变量中，9个变量对两个区域车辆损坏程度产生不同方向的影响，23个变量产生相同方向的影响，另外，12个变量仅对乡村有显著性影响，2个变量仅对城市有显著性影响。

关键字
卡车死亡事故；广义logit模型；风险因素；边际效应；交通安全

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