

Article

Severity Predictions for Intercity Bus Crashes on Highway Using a Random Parameter Ordered Probit Model

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Abstract: As intercity buses are a mode that moves large-scale occupancy between regions, it accounts for the mode share-means for mid- to long-distance movement in South Korea. However, the study of intercity bus safety needs to be more extensive, and safety policies are carried out based on traditional probability models without considering the data characteristics of bus accidents. Therefore, in this study, the Random Parameter Ordered Logit model was applied to derive fixed parameter factors that have the same effect on the severity of intercity bus accidents and Random Parameters that consider the heterogeneity of unique attributes by accident. It also analyzed the marginal effect of intercity bus accident severity. As a result of this study, the influencing factors that reflect heterogeneity with random parameters were driver's condition: drowsiness, vehicle size: medium, crash type: vehicle–pedestrian accident, road condition: wet pavement, and log form of AADT. The random parameter ordered logit model was traditionally found to be more suitable than the ordinal logit model, which only reflects fixed factors and more reliable predictions considering the heterogeneity of accident characteristics for each observation.

Keywords: intercity bus; accident; severity; probability model; Random Parameter; ordered logit; heterogeneity



Citation: Kim, K.; Hong, J. Severity Predictions for Intercity Bus Crashes on Highway Using a Random Parameter Ordered Probit Model. *Sustainability* **2023**, *15*, 13131. <https://doi.org/10.3390/su151713131>

Academic Editors: Itzhak Benenson and Victoria Gitelman

Received: 8 May 2023

Revised: 27 August 2023

Accepted: 29 August 2023

Published: 31 August 2023



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1. Introduction

Intercity buses refers to buses with a driving distance of more than 100 km, where more than 60% of the driving section is operated on the highway, and it has the characteristic that it does not stop between the origin and the destination according to Article 8 (6) of the Passenger Transport Service Act in South Korea [1]. Intercity buses driving on highways are a means of transportation that move more occupancies than passenger cars, causing numerous casualties and enormous socioeconomic losses in the event of a traffic accident.

According to the Korea Expressway Corporation's Highway Accident Report [2], as of 2021, 7436 intercity buses are registered in South Korea, and 32,064,311 bus trips annually transports 95,026,382 passengers across the country. In addition, intercity bus accidents on highways comprise 258 out of 6743 traffic accidents, accounting for only 3.8% of all highway accidents; however, the number of casualties is 179, accounting for about 21% of the 852 casualties caused by highway traffic accidents. These statistics show that the risk level of intercity bus accidents on highways is higher than that of other traffic modes, such as passenger cars.

Cases of accidents involving intercity buses in other countries show the enormous risks of bus accidents. In Southwestern France in 2015, 43 people were killed in a bus crash with a truck, and 20 people were killed when a bus overturned on wet roads in Bulgaria in 2018. Furthermore, a bus crashed into a guardrail on a highway in North Macedonia in 2021, killing 46 passengers [3]. According to the Road Safety Thematic Report [4], an analysis of bus and coach accidents in the European Union shows that the fatality rate on

highways is about 9%. In particular, statistics from Belgium confirmed that the fatality rate of buses is higher than that of heavy vehicle truck accidents. Between 2010 and 2017, the fatality rate of buses was 2.6 times greater than that of all 7.7 people, consisting of 14 people per billion vehicle kilometers on Belgian roads and 19.8 people per billion vehicle kilometers on buses. From 2008 to 2018, the fatality rate of intercity bus accidents on highways was found to be about 12% by NHTSA's Fatality Analysis Reporting System in the United States, and about 27,000 people were injured yearly due to bus accidents [5].

Therefore, to prepare for highway bus accidents that cause such high human damage, it is necessary to analyze existing accident data to discover factors and marginal effects that affect the severity of traffic accidents and emphasize the need for highway bus safety and policies based on these results.

Several existing studies have been conducted on traffic accident prediction and severity analysis, but studies focused on buses need to be more comprehensive. In addition, each bus accident was insufficient to consider the heterogeneity of the accident impact depending on the road environment, traffic conditions, vehicle characteristics, human behavior, and spatiotemporal characteristics exposed by the accident.

Many studies that discover the influencing factors of accident probability and severity assume that the influence of each independent variable in all accident observations is fixed. Thus, restricting variables that have different influences for each bus accident to one fixed coefficient value has the limitation of a biased result value.

Thus, to improve the model's limitations, built from existing references related to bus accidents, this study was expected to find more consistent analysis results by applying a random parameter methodology that can discover coefficient values considering the heterogeneity of variables affecting dependent variables.

This study collected raw data on highway bus accidents in Korea for five years, from 2012 to 2016, and explored factors that affect the severity of accidents by using the Random Parameter Ordered Probit Model methodology. Figure 1 shows the South Korean highway network, and the data on accidents on the highway include information on time and location, roadside features, weather, pavement condition, vehicle and driver, and road geometry for each accident. In addition, we tried to identify fixed parameters that have the same effect on the severity of bus accidents regardless of the individual characteristics of all observations and random parameters that reflect heterogeneity and analyze the marginal effect of each variable to present findings for bus safety.



Figure 1. Network of South Korean highway.

2. Literature Review

Existing studies on bus accidents mainly used the ordinal logit (or probit) method of the probability model to analyze the probability and severity of traffic accidents. Various methodologies have been applied, such as association rule mining, meta-analysis, random parameter multi-logit model, and multiple-level mixed-effect logit model. Bhin and Son [6] discovered factors affecting the severity of accidents according to the gender of bus drivers (all men and women) using decision trees and ordinal logit models. As a result, the factors that increase the severity of accidents for all drivers and male drivers are vehicle-to-vehicle accidents, speeding, and median enforcement. For female drivers, minimum safety distance was a factor affecting the severity. Kim et al. [7] conducted a meta-analysis to find factors affecting the severity of city bus accidents. Variables such as speed violation, drinking, speed limit (100 km/h or higher), vehicle-vehicle, nighttime, drowsiness, curved alignments, and driver's age were found to have a significant impact on the severity of city bus accidents. Using the ordinal logit model, Bhin and Son [8] analyzed the factors influencing the severity of accidents according to bus type and repetitive accident, and variables such as vehicle-person, speed violation, and signal violation were found to have a significant impact. Lee et al. [9] tried to contribute to establishing safer intercity bus policies by developing an accident model for each type of expressway bus accident (driver factor, road, environmental factor, and other factors) through the probability regression model. As a result, in the human factor model, the driver's age and driving experience (more than ten years) were found to be influential factors; significant factors of road and environmental factor models are road conditions (wet and freezing), weather (cloud), nighttime, longitudinal gradients (longer than 5%), and straight road (500 m or more). In other factor models, the number of vehicles and vehicle-vehicle variables affect the severity of the highway bus accident. By applying association rule mining techniques, Samerei et al. [10] discovered variables related to fatal bus accidents in Australia. They found that the presence of pedestrians, female drivers, and road sections with dark vision were highly related to fatal bus accidents on weekends. Nguyen et al. [11], using the ordinal logit model, presented nighttime, the number of lanes (above the third lane), weather (rain), and local areas as factors affecting the severity of bus accidents in Hanoi, Vietnam. Yoon et al. [12] tried to find the cause affecting the severity of city bus accidents by applying an ordinal logit model. As a result, it was found that the factors increasing the severity of the city bus accident were speed (less than 70 km/h), lane width (less than 3 m), curve alignments (left, right), and road conditions (wet). In contrast, the factors that reduced the accident's severity were peak hours, snow, or road conditions (freezing).

Shen et al. [13] used an ordered probit model to find factors influencing the severity of bus accidents in the U.K., and they suggested variables with significant effects on collisions (head-on), road (wet), and speed limits. Wang et al. [14] analyzed the impact of collision accidents among the characteristics of individual bus drivers by applying a random effect two-level (level 1—driver, level 2—vehicle) logit model methodology. The result of the model establishment represents that drivers' age (46–55), aggressive and violent drivers, and the presence of insomnia were influencing factors at the driver level, and weather condition variables at the vehicle level affected bus accidents. Kaplan and Prato [15] used an ordered logit model to extract risk factors for the severity of British bus accidents. The analysis showed variables such as driver's age (under 25, over 65), speed limit (over 65 mph, less than 20 mph), and intersection were found to affect the severity of the bus accident. Damsere-Derry et al. [16] analyzed Ghana's severity of intercity bus accidents using a random parameter multi-logit model. The result suggested variables such as driver's age (60 or older), speeding, poor overtaking, careless driving, and inexperienced driver's career were found to be influencing factors. Nasri and Aghabayk [17] tried to find risk factors for the severity of bus accidents in Mashhad by applying the ordinal logit method, and angle and swipe variables among the types of collision accidents were derived as influencing factors. Finally, Saha et al. [18] used the Latent segmentation-based ordered logit method to derive factors influencing the severity of the public transit crash in Bangladesh Dhaka.

They revealed that variables such as police control, female victims, and adult victims were influencing variables.

In addition, research was conducted using ordered (probit) random parameters to consider the characteristics of each type of accident, such as vehicle type (truck, general vehicle), accident type (backward collision, single accident-left and right road departure, rollover accident, angle collision), road type (two-lane rural road), and age (elderly and youth) [19–28]. In existing studies, the random parameter model has been widely applied in analyzing traffic accidents. However, it has been mainly used to analyze the probability and severity of car or truck accidents, and only some existing studies have focused on bus accidents. In the study of [29], the multivariate random-parameters Tobit model was applied to analyze the accident rate by road injury severity, and in the study of Ijaz et al. [30], factors that affect the accident severity of motorcyclists were derived by considering variables with heterogeneity. Existing studies have used the random parameter methodology to argue that traffic accidents are mainly caused by drivers' traffic behavior, such as speeding and changing lanes, and these factors have heterogeneity, so they show various influences according to road sections or temporal characteristics [20,22,31].

As a result of the existing literature review, previous studies related to accident severity according to various bus types have been attempted. However, most of them focused on the factors influencing the severity of bus accidents and the development of a prediction model based on traditional probability models. In particular, in depth studies were conducted to reflect the heterogeneity of accident-influencing factors in various accident-related studies. For intercity buses, it was found that research was necessary considering the traffic characteristics of the studied area's spatial- and environmental-affecting effects for each accident. Therefore, this study collected and analyzed data on various potential factors such as spatiotemporal characteristics, vehicle and human characteristics, road environment, and the traffic environment of highway sections that affect highway bus severity. Furthermore, to consider the heterogeneity of the impact of highway bus accidents, the random parameter ordered probit model is applied to find variables with fixed probability parameters and random probability parameters of highway bus accident severity and to define each effect.

3. Methods

In order to analyze the characteristics of factors affecting each severity of intercity bus accidents, the level of accidents was classified into physical damage and injury (serious injury and fatal), and a random parameter ordered probit model was used to explain the indexed characteristics of the severity of the accident. Existing studies have used a probit model that assumes the variance of the error term distribution is the same, and a normal distribution with zero covariance follows the covariance [32–38]. Since the probit model predicts binomial ($y = 0 \text{ or } 1$), it was based on the random parameter ordinal probit model to be found through dependent variables y' considering random probabilities based on modeling the accident severity of each observation of the ordinal ($y = 0, 1, 2, 3 \dots$). Then, Equation (1) is a random parameter ordered probit model.

$$y' = \beta'X + \varepsilon \quad (1)$$

Here, X is the vector value of the independent variable, β' is the Vector value of the estimable parameter, and ε is a random error term assumed to follow a normal distribution of observations with mean 0 and variance 1.

In Equation (2), the independent variable y is defined as follows by the unobserved variable y' .

$$y = \begin{cases} 3 & \text{if } y' \geq \mu_2 & (\text{severe injury}) \\ 2 & \text{if } \mu_1 < y' \leq \mu_2 & (\text{evident injury}) \\ 1 & \text{if } \mu_0 < y' \leq \mu_1 & (\text{possible injury}) \\ 0 & \text{if } y' < \mu_0 & (\text{no injury}) \end{cases} \quad (2)$$

Here, $\mu_0 = 0$, and μ_2 are thresholds jointly estimated with β' parameters. The probability of severity for each variable may be expressed as a distribution of random error terms ε .

$$\begin{aligned} P(y = 3) &= 1 - \Phi(\mu_2 - \beta'X) \\ P(y = 2) &= \Phi(\mu_2 - \beta'X) - \Phi(\mu_1 - \beta'X) \\ P(y = 1) &= \Phi(\mu_1 - \beta'X) - \Phi(\mu_0 - \beta'X) \\ P(y = 0) &= \Phi(\mu_0 - \beta'X) \end{aligned} \quad (3)$$

However, the standard probit model can treat β' parameters as constant values through observations, resulting in potentially biased results, which limits each variable to have the same effect on all individual observations. Therefore, considering this point, the random parameter ordered probit model was applied to discover unobserved heterogeneity through randomly distributed error terms Φ .

$$\beta' = \beta + \Phi \quad (4)$$

Since the interpretation of the estimated coefficient values β for the accident severity is not simple, the effect of a unit-by-unit change in the independent variable on the probability of the accident severity measures the marginal effect. Random-parameter ordered probit models are typically used to measure the effect of variables at the level of accident severity while keeping all other variables constant, and the marginal effects can be expressed as follows.

$$\begin{aligned} \frac{\partial P(y = 3)}{\partial X} &= \Phi(\mu_2 - \beta'X)\beta \\ \frac{\partial P(y = 2)}{\partial X} &= [\Phi(\mu_1 - \beta'X) - \Phi(\mu_2 - \beta'X)]\beta \\ \frac{\partial P(y = 1)}{\partial X} &= [\Phi(\mu_0 - \beta'X) - \Phi(\mu_1 - \beta'X)]\beta \\ \frac{\partial P(y = 0)}{\partial X} &= \Phi(\mu_0 - \beta'X)\beta \end{aligned} \quad (5)$$

4. Results

4.1. Descriptive Statistics

The random parameter ordered probit model was applied to find fixed and random parameters that reflect heterogeneous observation characteristics, and the results showed that the coefficient value of each independent variable might have a variety of values by reflecting the unique characteristics of the variable.

For the analysis of this study, raw intercity bus crash data on highways in South Korea from 2012 to 2016 were used. Furthermore, independent variables potentially affecting highway bus crashes were classified into spatiotemporal factors, human and vehicle factors, and road and traffic environment factors, as shown in Table 1. The collected independent variables are dummy variables with binomial values such as 1 (corresponding) or 0 (not applicable), including continuous variables such as Log-AADT. In addition, the dependent variable, Intercity Bus Accident Severity, was ordered, and it was defined as the value of 0 if the accident was a physical damage accident, 1 if it was an injury accident, and 2 if it was a severe and fatal accident.

A probability model consisting of fixed and random parameter variables was established by applying various independent variables that can affect the severity of intercity bus accidents, such as AADT and spatiotemporal (segment type, day, and time) factors presented in Table 1. The significance of each parameter was determined at a significance level of 90% ($p\text{-value} \leq 0.1$) in consideration of the number of samples, and probability distributions such as normal distribution, uniform distribution, and exponential distribution were considered to estimate the coefficient of the random parameter model. Through applying various probability distributions for each independent variable, this study found that variables were most significant when assumed to be a normal distribution. In addition, variables with the significance of the standard deviation for the random parameter distribution were identified, and the hypothesis that the factor variables affecting each observation were heterogeneous was supported through the corresponding result value.

Table 1. Summary statistics for effect factors of crash occurrence.

Category	Definition of Variables	Avg.	Std.
Spatial-temporal factors	1 if an intercity bus crashes in main lane; otherwise 0.	0.731	0.443
	1 if an intercity bus crashes in ramp; otherwise 0.	0.108	0.310
	1 if an intercity bus crashes in tollgate; otherwise 0.	0.100	0.300
	1 if an intercity bus crashes in tunnel; otherwise 0.	0.050	0.217
	1 if an intercity bus crashes in the other; otherwise 0.	0.011	0.053
	1 if an intercity bus crashes in guardrail shoulder; otherwise 0.	0.435	0.496
	1 if an intercity bus crashes in guardrail fence; otherwise 0.	0.007	0.084
	1 if an intercity bus crashes in none of guardrail; otherwise 0.	0.350	0.477
	1 if an intercity bus crashes in concrete; otherwise 0.	0.094	0.292
	1 if an intercity bus crashes in the other; otherwise 0.	0.114	0.107
	1 if an intercity bus crashes due to vehicle defects; otherwise 0.	0.082	0.274
	1 if an intercity bus crashes due to negligence; otherwise 0.	0.257	0.437
	1 if an intercity bus crashes due to speeding; otherwise 0.	0.223	0.416
	1 if an intercity bus crashes due to drowsiness; otherwise 0.	0.096	0.295
Human and vehicle factors	1 if an intercity bus crashes due to flat tire; otherwise 0.	0.071	0.258
	1 if an intercity bus crashes due to obstacle; otherwise 0.	0.096	0.295
	1 if an intercity bus crashes due to safety distance violation; otherwise 0.	0.039	0.192
	1 if an intercity bus crashes due to the other; otherwise 0.	0.136	0.097
	1 if an intercity bus crashes due to normal; otherwise 0.	0.922	0.268
	1 if an intercity bus crashes due to tired; otherwise 0.	0.040	0.197
	1 if an intercity bus crashes due to drinking; otherwise 0.	0.020	0.141
	1 if an intercity bus crashes due to the other; otherwise 0.	0.017	0.045
	1 if the small size of intercity bus crashes; otherwise 0.	0.488	0.500
	1 if the medium size of intercity bus crashes; otherwise 0.	0.278	0.448
	1 if the big size of intercity bus crashes; otherwise 0.	0.212	0.409
	1 if the other size of intercity bus crashes; otherwise 0.	0.022	0.146
	1 if the type of intercity bus crash is vehicle-object; otherwise 0.	0.546	0.498
	1 if the type of intercity bus crash is vehicle-vehicle; otherwise 0.	0.239	0.427
Roadway and environmental factors	1 if the type of intercity bus crash is vehicle-pedestrian; otherwise 0.	0.012	0.108
	1 if the type of intercity bus crash is other; otherwise 0.	0.203	0.278
	1 if the bus driver is 20–29 s; otherwise 0.	0.057	0.231
	1 if the bus driver is 30–39 s; otherwise 0.	0.269	0.444
	1 if the bus driver is 40–49 s; otherwise 0.	0.135	0.342
	1 if the bus driver is 50–59 s; otherwise 0.	0.206	0.404
	1 if the bus driver is 60–69 s; otherwise 0.	0.227	0.419
	1 if the bus driver is 70 s; otherwise 0.	0.107	0.174
	1 if the intercity bus crashes in rates of car; otherwise 0.	0.684	0.075
	1 if the intercity bus crashes in rates of truck; otherwise 0.	0.038	0.018
	1 if the intercity bus crashes in rates of bus; otherwise 0.	0.277	0.076
	1 if the intercity bus crashes on moisture of road surface; otherwise 0.	0.272	0.445
	1 if the intercity bus crashes on dry road surface; otherwise 0.	0.717	0.451
	1 if the intercity bus crashes on icy road surface; otherwise 0.	0.011	0.069
Roadway and environmental factors	1 if the intercity bus crashes in snow; otherwise 0.	0.049	0.216
	1 if the intercity bus crashes in fine weather; otherwise 0.	0.596	0.491
	1 if the intercity bus crashes in the rain; otherwise 0.	0.207	0.405
	1 if the intercity bus crashes in cloudy weather; otherwise 0.	0.137	0.344
	1 if the intercity bus crashes in other; otherwise 0.	0.011	0.027
	1 if the intercity bus crashes in spring; otherwise 0.	0.239	0.427
	1 if the intercity bus crashes in summer; otherwise 0.	0.278	0.448
	1 if the intercity bus crashes in fall; otherwise 0.	0.245	0.430
	1 if the intercity bus crashes in winter; otherwise 0.	0.237	0.425
	Annual average daily traffic volumes (vehs/day)		
	Log (AADT)	10.704	0.785

The log-likelihood function was used as an indicator to determine the model's goodness of fit of the finally selected severity prediction model of intercity bus accidents. The log-likelihood function generally indicates that the closer the value is to 0, the higher the model fit. As a result of the analysis of this study, the Restricted Log-likelihood value, including only the constant term, was -2374.412 , and the log-likelihood of the Fixed Parameter model was improved to -2057.16 . In contrast, the log-likelihood of the random parameter model was -2000.367 , finding that the model's suitability was somewhat improved.

Independent variables (ramps, toll gates, negligence, flat tire, obstacle defects, drowsiness, condition of driver (a normal condition), rain, vehicle–vehicle accident, guardrail, vehicle size (small, medium), driver's age—30 s, vehicle type (truck), summer, road condition (wet), and log-AADT) were statistically found to be significant at a 90% significance level. Among them, the variables (road condition (wet), vehicle size (medium), log-AADT, vehicle–pedestrian accident, and drowsiness) were adopted as significant variables in random parameters, which had a heterogeneous effect on the severity of bus accidents. The results of the traditional ordered probit model and the random parameter ordered probit model for the factors affecting the severity of highway bus accidents are shown in Tables 2 and 3, respectively.

Table 2. Ordered Probit Model of Intercity bus crash severity.

Variable	Estimate	Odds Ratio	Std. Err	t-Stat
Constant	−1.473 ***	0.229	0.353	−4.178
Ramp (1 if ramp segment; 0 otherwise)	−0.355 ***	0.701	0.087	−4.074
Tollgate (1 if tollgate; 0 otherwise)	−0.711 ***	0.491	0.098	−7.268
Negligence (1 if driver is negligent; 0 otherwise)	0.147 ***	1.158	0.060	2.443
Flat tire (1 if bus tire is flat; 0 otherwise)	0.275 ***	1.317	0.097	2.841
Obstacle (1 if obstacle on the freeway; 0 otherwise)	−0.867 ***	0.420	0.124	−6.995
Drowsiness (1 if driver is drowsy; 0 otherwise)	0.226 ***	1.254	0.086	2.619
Small (1 if bus size is small; 0 otherwise)	−0.316 ***	0.729	0.062	−5.078
Medium (1 if bus size is medium; 0 otherwise)	−0.246 ***	0.782	0.068	−3.634
Vehicle–vehicle (1 if a vehicle to vehicle crash; 0 otherwise)	0.739 ***	2.095	0.060	12.358
Vehicle–pedestrian (1 if a vehicle to pedestrian crash; 0 otherwise)	2.134 ***	8.445	0.208	10.255
normal (1 if the driver's condition is normal; 0 otherwise)	−0.342 ***	0.711	0.089	−3.820
Rainy (1 if it rains; 0 otherwise)	0.234 **	1.264	0.106	2.203
Guardrail fence (1 if guardrail fence exists; 0 otherwise)	−0.639 **	0.528	0.315	−2.025
30s (1 if driver's age ≥ 30 and < 40 ; 0 otherwise)	−0.173 ***	0.841	0.058	−2.981
Rate of Truck volume (truck volume/total volume at the crash point)	2.882 **	17.843	1.335	2.159
Summer (1 if the season is summer; 0 otherwise)	−0.160 ***	0.852	0.055	−2.884
Moisture (1 if moisture on the pavement; 0 otherwise)	−0.334 ***	0.716	0.097	−3.434
Log AADT (logarithm of AADT)	0.134 ***	1.143	0.031	4.265
Log-likelihood function = -2057.160				
Number of observations = 3064				
Restricted Log-likelihood function = -2374.412				

*** 99% confidence level, ** 95% confidence level.

Table 3. Random Parameter Ordered Probit Model of Intercity bus crash severity.

Variable	Estimate	Odds Ratio	Std. Err	t-Stat
Constant	−1.534 ***	0.216	0.354	−4.328
Ramp (1 if ramp segment; 0 otherwise)	−0.366 ***	0.693	0.089	−4.130
Tollgate (1 if tollgate; 0 otherwise)	−0.740 ***	0.477	0.097	−7.662
Negligence (1 if driver is negligent; 0 otherwise)	0.149 ***	1.161	0.062	2.399
Flat tire (1 if bus tire is flat; 0 otherwise)	0.292 ***	1.339	0.093	3.140
Obstacle (1 if obstacle on the freeway; 0 otherwise)	−0.884 ***	0.413	0.126	−6.987
Drowsiness (1 if driver is drowsy; 0 otherwise)	0.213 ***	1.237	0.088	2.421
Standard deviation of parameter	0.307 ***	1.360	0.074	4.150
Small (1 if bus size is small; 0 otherwise)	−0.322 ***	0.725	0.063	−5.131

Table 3. Cont.

Variable	Estimate	Odds Ratio	Std. Err	t-Stat
Medium (1 if bus size is medium; 0 otherwise)	−0.290 ***	0.748	0.070	−4.156
Standard deviation of parameter	0.326 ***	1.386	0.048	6.825
Vehicle–vehicle (1 if a vehicle to vehicle crash; 0 otherwise)	0.762 ***	2.143	0.062	12.288
Vehicle–pedestrian (1 if a vehicle to pedestrian crash; 0 otherwise)	2.231 ***	9.307	0.219	10.175
Standard deviation of parameter	0.432 **	1.540	0.212	2.035
normal (1 if the driver’s condition is normal; 0 otherwise)	−0.359 ***	0.698	0.087	−4.137
Rainy (1 if it rains; 0 otherwise)	0.243 **	1.275	0.110	2.206
Guardrail fence (1 if guardrail fence exists; 0 otherwise)	−0.652 *	0.521	0.384	−1.698
30s (1 if driver’s age ≥ 30 and <40 ; 0 otherwise)	−0.178 ***	0.837	0.061	−2.938
Rate of Truck volume (truck volume/total volume at the crash point)	3.008 **	20.252	1.414	2.128
Summer (1 if the season is summer; 0 otherwise)	−0.166 ***	0.847	0.057	−2.943
Moisture (1 if moisture on the pavement; 0 otherwise)	−0.377 ***	0.686	0.100	−3.784
Standard deviation of parameter	0.281 ***	1.324	0.050	5.596
Log AADT (Logarithm of AADT)	0.141 ***	1.152	0.032	4.479
Standard deviation of parameter	0.012 ***	1.012	0.002	5.400
Log-likelihood function = −2000.367				
Number of observations = 3064				
Restricted Log-likelihood function = −2374.412				

*** 99% confidence level, ** 95% confidence level, * 90% confidence level.

4.2. Results of the Random Parameter Model

Variables with heterogeneity selected as random parameters under normal distribution can calculate probabilities using statistically significant mean and standard deviation values, confirming the distribution of how each random parameter affects the severity of intercity bus accidents, as shown in Figure 2.

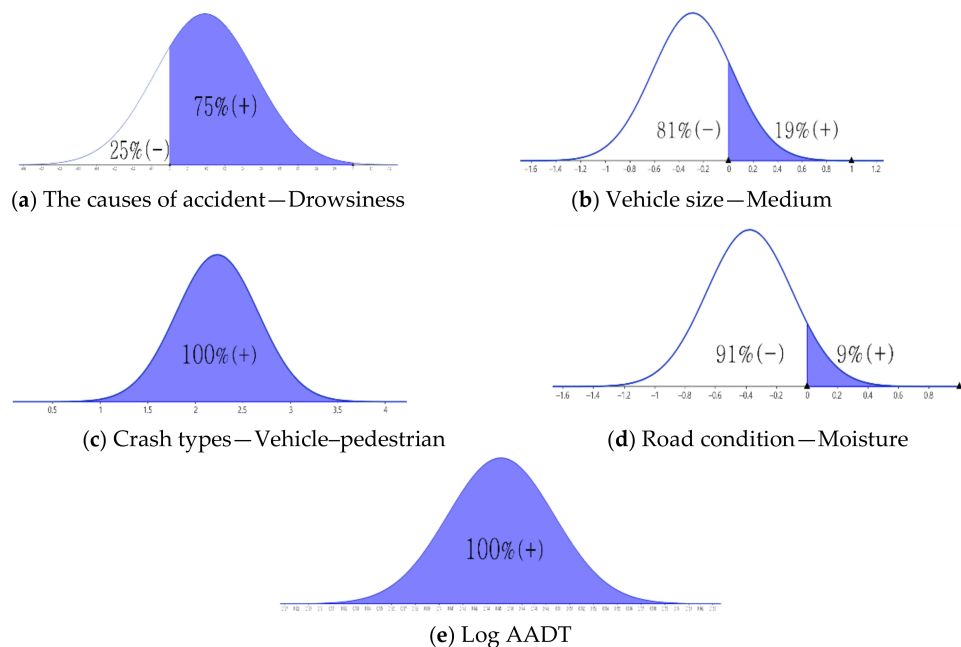


Figure 2. Parameter distribution of random parameter variable.

Random parameters with heterogeneity between bus accident characteristics for each observation take the form of a normal distribution and can calculate the probability of an accident through statistically significant mean and standard deviation values. In other words, assuming both fixed and random parameters of each variable, it was determined that the variable was heterogeneous as a random parameter when the estimated value of the random parameters statistically satisfied the 95% confidence level. The explanation of

how each random parameter derived through this analysis has a heterogeneous effect on the severity of the bus accident is as follows.

The drowsiness variable has an average value of 0.213 standard deviations of 0.037. Based on the normal distribution, as shown in Figure 2a, it was found that about 75% of intercity bus accidents caused by drowsiness increased the severity of accidents, and the remaining 25% decreased the severity. These results show that drowsiness is a factor that increases the severity of accidents such as road departures [39,40]. However, some drowsiness accidents occur in situations where there is not much traffic, such as nighttime, and, in particular, it is expected to have a negative (−) effect on the severity of the accident as it is highly likely to occur in association with single accidents and physical damage accidents such as collisions with road obstacle.

The intercity bus's vehicle size (medium) variable has an average value of −0.290 with a standard deviation of 0.07. Figure 2b shows that about 19% of the bus accidents under normal distribution have a positive (+) effect on the accident's severity, and the remaining 81% have a negative (−) effect. In the case of truck accidents proposed in some existing studies, it can be seen that the degree of impact varies depending on the size of the truck and unit [41,42]. Since the size of vehicles on the highway is proportional to the number of passengers, fatal casualties increase. However, in large buses with many passengers, drivers tend to avoid over-speeding, which can reduce the severity of an unexpected accident.

The vehicle–pedestrian accident variable had an average value of 2.231 and a standard deviation of 0.432, and according to the normal distribution, 100% of bus accidents had a positive (+) effect on the severity of the accident, as shown in Figure 2c. This result shows consistency with existing studies that vehicle–pedestrian accidents increase the severity of accidents [43,44]. As the vehicle drives at high speed, the risk of severe injury and fatality in a collision with a pedestrian is expected to be very high.

The road condition (wet) variable has an average value of −0.377 and a standard deviation 0.281. While 9% of the observations caused an increase in the severity of bus accidents, 91% were found to decrease in Figure 2d. There are results of existing studies that increase the severity of the accident [45,46], but there are conflicting results that the road condition (wet) reduces the severity [35,44,47]. Although accidents in road conditions (wet) may increase the severity of the accident due to increased braking distance when braking on slippery roads, which can increase the severity of the accident due to a front collision with the median barriers and a rear collision with the car in front, the occurrence and severity of accidents decrease since the driver can alter the effect by focusing more on safe driving based on preliminary information on the risk of highway accidents, such as weather forecasts, navigation, and highway information.

The log-AADT variable was significant for random parameters under a normal distribution. As shown in Figure 2e, All observations were found to have a positive (+) relationship with the severity of the bus accident, with an average value of 0.141 and a standard deviation of 0.012 parameters. This result showed contradictory results from existing studies that the impact of traffic on the spatial scope is a factor that increases or decreases the severity of accidents [48,49]. The increase in log-AADT means frequent conflicts between vehicles and buses on highways exist. Therefore, thorough highway reinforcement and a thorough highway crackdown and control, the severity is reduced. However, if an accident occurs in proportion to traffic volume, the injuries are expected to be enormous due to secondary accidents such as chain collisions.

4.3. Results of Fixed Parameter Model

Each fixed parameter variable derived through the random parameter ordered probit model has a homogeneity in effect on all observations, and the interpretation of the results is as follows.

First, the severity of bus accidents in the ramp and tollgate segment was 0.693 and 0.477 times higher than in other accident segments. According to the results of the fundamental statistical analysis, bus accidents in the main-lane segment are the highest at

73% of all accidents. In particular, the main-lane segment is more likely to have various driving risk behaviors, such as speeding and a negligence of Safe Driving than the ramp and tollgate segment. Hence, the severity of accidents is higher than in other segments.

Second, the severity of bus accidents caused by vehicle–vehicle on highways was 1.953 times higher than vehicle (single). Vehicle–vehicle accidents strongly influence the severity of accidents in proportion to the degree of collision between vehicle–vehicle and the number of passengers in the vehicle. Therefore, they are more likely to have greater severity and damage than a single (vehicle) caused by a collision with facilities.

Third, the probability of bus accident severity according to small size was 0.7 times higher than large buses. Large buses have many occupancies, which can cause more damage than small buses in the event of an accident. Thus, it is necessary to develop situational awareness and decision abilities for drivers of large vehicles so that passengers can safely escape the dangerous situation.

Fourth, the probability of the severity of a bus accident when the driver's condition is normal was 0.698 times lower than an abnormal driver, such as one who has been drinking or had an illness. In general, drivers in normal conditions instinctively make motions that can minimize the accident's severity when facing unexpected situations, so the accident's severity is higher than abnormal driver conditions such as drinking and diseases.

Fifth, it was found that the severity of bus accidents at guardrails was 0.519 times lower than at other barrier facilities. Guardrails play a significant role in preventing secondary accidents such as median encroachment and falling in advance. Thus, the checking and inspecting of road safety facilities such as guardrails in sections with high frequency or high severity of bus accidents should be performed periodically.

Sixth, it was discovered that the probability of a severe bus accident in rainy weather was 1.193 times higher than in other weather. Highways have systematically responded to dangerous situations to enable safer driving by expressing lowered speeds depending on road conditions such as wet and ice through variable speed limits (VSL). If it rains on the highway, securing a view with the front vehicle is impossible, which may lead to a secondary accident due to a collision. In addition, it is necessary to induce the safe driving behavior of bus drivers to comply with the laws that reduce the speed limit as the available range of view decreases.

Seventh, the driver's age being 30 was found to reduce the severity of bus accidents by 0.847 times. Since drivers aged 30 are physically healthier than elderly drivers, they accumulate less fatigue when driving for a long time and take less time to recognize and respond to the situation than elderly drivers. Finally, the summer dummy variable was found to lower the probability of accident severity by 0.841 times. In summer, there is no slippery road surface, such as freezing caused by snow and heavy snow in winter, so it is lower in severity than in other seasons, such as winter.

Finally, the severity of bus accidents caused by negligence and flat tires was 1.184 times and 1.278 times higher than other causes of accidents. Since the human cause of most accidents on highways is negligence, policy establishment such as improving safety driving awareness for drivers is needed to address the problem of increasing the accident's severity.

5. Discussion

In this study, marginal effects were estimated to intuitively understand the effect of independent variables in the built model on dependent variables (severity—physical damage, injury, serious injury, and fatal). The marginal effect refers to the degree of change in the dependent variable's severity value when the independent variable's value changes by one unit or the value of the dummy variable changes from 0 to 1 or 1 to 0. The values of the marginal effect for each variable through the developed model are summarized as shown in Table 4.

Table 4. The marginal effect of random parameter ordered probit prediction model.

Variable	Fatal and Severe Injury	Minor Injury	Property Damage Only
Ramp	−0.013	−0.103	0.116
Tollgate	−0.020	−0.188	0.208
Negligence	0.007	0.045	−0.052
Flat tire	0.018	0.089	−0.107
Obstacle	−0.021	−0.214	0.235
Drowsiness	0.012	0.065	−0.077
Vehicle size—Small	−0.015	−0.096	0.111
Vehicle size—Medium	−0.012	−0.085	0.096
Vehicle—vehicle	0.055	0.226	−0.281
Vehicle—pedestrian	0.533	0.132	−0.665
Driver’s condition—normal	−0.023	−0.110	0.133
Rainy	0.013	0.074	−0.087
Guardrail fence	−0.016	−0.163	0.179
Driver’s age—30s	−0.008	−0.053	0.060
Rate of Truck	0.139	0.901	−1.040
Summer	−0.007	−0.049	0.056
Pavement-Moisture	−0.015	−0.109	0.124
Log AADT	0.007	0.042	−0.049

The severity of physical damage accidents in the ramp and tollgate segments increased by 11.56% and 20.75%, respectively. However, the severity of injury accidents decreased by 10.8% in the ramp, 17.8% in the tollgate segment, and 1.6% and 2.2% in each facility.

Vehicle–vehicle accidents increased injury severity by 19.4% and fatal and severe accidents by 5.2%, while physical damage accidents decreased by 24.6%.

Small-size bus accidents increased the severity of injuries, serious injuries, and fatalities by 10.4% and 1.9%, while medium-sized buses decreased these by 9.6% and 1.6%, respectively. As the proportion of trucks in the highway segment increased, the severity of injuries and fatal and severe accidents for intercity buses increased to 98.7% and 18%, respectively.

When the driver’s condition was normal and the age was 30s, the severity of physical accidents on the bus increased by 13.3% and 5.6%, respectively. On the other hand, bus severity on guardrails decreased by 16.1% and 1.9%, respectively, for injuries, serious injuries, and fatalities.

When it was summer or road conditions (wet), physical damage increased the severity by 5.8% and 10.9%. Nevertheless, injuries, serious injuries, and fatalities in the summer were expected to decrease by 5% and 0.9%, and road conditions (wet) by 9.4% and 1.5%, respectively. Contrary to the discovered result earlier, the severity of physical damage accidents in rain decreased by 6.3% compared with other weather, but injuries, serious injuries, and fatalities increased in severity by 5.2% and 1%.

It was found that the increase in log-AADT increased the severity of injury, serious injury, and fatal accidents, while the severity of physical damage accidents decreased.

Finally, the severity of physical damage accidents caused by negligence, flat tire, and drowsiness decreased by 6%, 8.9%, and 6.9%, respectively, but increased by 24.2% for road obstacles.

Through this analysis, the ramp section, careless driving, drowsy driving, vehicle size (small), vehicle–pedestrian accident, rainy weather, drivers in their 30s, wet road conditions, and AADT variables derived as factors affecting the severity of intercity bus accidents were found to be consistent with the results of previous bus accident studies. In particular, AADT derived from random parameters was found to be a factor that increased death and serious accidents. The results of the marginal effect show that AADT has a different effect on accident severity due to segment heterogeneity but has a more significant impact on fatal and serious injury accidents and minor injuries [50,51]. On the other hand, unlike the results of Damsere-Derry et al. [16]. This study found that the smaller the size of the

bus, the lower the accident's severity. In addition, drivers in their 30s were found to have a lower severity of accidents than other age groups, contrary to Chu [52]'s study, indicating heterogeneous results depending on regional or traffic environment factors.

Several existing studies [53–55] have found that vehicle speed affects accident severity. However, in this study, it was not reflected because it was challenging to collect the speed data of the accident vehicle, so it will be necessary to add and analyze speed variables in the future.

6. Conclusions

This study tried to overcome the limited point of existing studies that do not consider the heterogeneity of influencing factors derived from the ordinal logit (or ordinal probit) model and to improve the reliability of the severity analysis of highway bus accidents.

Among the factors affecting the severity of highway bus accidents, we identified the difference between the existing probability model by deriving Fixed Parameters with homogeneous effects and random parameters with heterogeneity. Raw data on highway bus accidents in Korea for five years, from 2012 to 2016, were used in the analysis of this study. We identify the difference between the existing probability model and the random parameter probit model, which has Fixed Parameters with homogeneous effects and random parameters with heterogeneity.

Among the variables that significantly affect the severity of highway bus accidents, it was found that drowsiness, vehicle size (medium), vehicle–pedestrian accidents, road condition (wet), and log-AADT had a heterogeneous effect on highway bus accident severity.

Based on the random parameter variable results, the severity of the intercity bus accident and the implications derived from each variable are as follows.

The vehicle–pedestrian accident and log-AADT were found to have a 100% positive (+) effect on the severity of bus accidents. As intercity buses run higher than 100 km/h, there is a high possibility of death or severe damage in a collision with a person. In addition, the higher the AADT, the more crowded it is. Consequently, it can cause secondary accidents continuously, so the damage caused by the accident is expected to increase.

Among the vehicle size (medium) of intercity buses, it was confirmed that 19% of bus accidents had a positive effect on the severity of the accident, and the remaining 81% had a negative effect. As vehicle size affects the number of passengers on board in proportion to the size of the vehicle, casualties may increase in the event of an accident. However, the higher the number of passengers on board, the stronger the driver's sense of responsibility, which may induce the driver to drive safely.

The road condition (wet) increased the severity of bus accidents by about 9% of bus accidents, but the other 91% had a decreased severity. Road condition (wet) creates a slippery road environment, which can increase the risk of accidents due to chain collisions. Nevertheless, it can increase the driver's concentration on safe driving based on real-time information transmission media for the road environment, such as weather forecasting and navigation.

Finally, intercity bus accidents caused by drowsiness increased the severity by about 75% while reducing it by 25%. Drowsiness can increase the severity of the accident due to lane departure. Nevertheless, some accidents caused by drowsiness are likely to occur alone in the early morning when there is not much traffic volume, so unlike other conditions of drivers, such as being drunk, it is expected to have a negative impact on the severity of the accident.

As evidenced by the results of this study, the severity of intercity bus accidents has the effect of heterogeneously influencing factors for each observation. So, unlike the existing safety policies, various policies will be needed to promote intercity bus safety by identifying the characteristics of each accident. The intercity bus crash influencing factors derived from this analysis contribute to establishing alternatives and policies to prevent future accidents. They are expected to be evaluated before and after the safety policy is implemented through the simulator [55,56]. This can also be used as significant data on safety when developing

autonomous bus simulations in the future. Therefore, an advanced bus safety prediction model is expected to be developed in the future by considering the heterogeneity of spatial and temporal aspects according to (routes and year) and factors affecting the severity of bus accidents. In addition, an even higher performance traffic accident prediction model is expected to be developed as this study does not consider the additional analysis of the driver's traffic behavior [30] and speed.

Author Contributions: Conceptualization, J.H.; methodology, J.H. and K.K.; software, K.K.; validation, J.H. and K.K.; formal analysis, K.K.; investigation, J.H.; data curation, J.H.; writing—original draft preparation, K.K.; writing—review and editing, J.H.; visualization, K.K.; supervision, J.H.; funding acquisition, J.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Bisa Research Grant of Keimyung University in 2021 (No.20210371).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be available on request.

Conflicts of Interest: The authors declare no conflict of interest.

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