Exploring Impacts of Factors Contributing to Injury Severity at Freeway Diverge Areas

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A study was done to identify factors contributing to injury severity at freeway diverge areas and to evaluate impacts of the factors. Crash data and roadway information were collected at 231 freeway exit segments in Florida. Injury severity prediction models were developed by using partial proportional odds regression, which relaxes the restriction that all regression coefficients be the same across output values and allows one or more regression coefficients to differ across outcome levels. The analysis results indicated that the partial proportional odds model is more flexible and provides much better results than does the ordered probit model for fitting injury severity data. Factors that significantly influence injury severity at freeway diverge areas include length of deceleration and ramp lanes, curve and grade at diverge areas, light and weather conditions, alcohol or drug involvement, heavy-vehicle involvement, number of lanes on main lines, average daily traffic on main lines, surface condition, land type, and crash type. It can also be concluded that exit ramp types (single-lane exit ramps, single-lane exit ramps with a taper, two-lane exit ramps with an optional lane, and two-lane exit ramps without an optional lane) have no significant effects on injury severity at freeway diverge areas.

Freeway diverge areas in the vicinity of exit ramps are considered critical elements of freeways, where intensive lane-changing maneuvers due to exiting traffic cause disturbance to through traffic on the freeway main lines. This disturbance may result in traffic conflicts, increase the probability of crash occurrence, and even aggravate crash injury severity. Identifying factors that contribute to injury severity at freeway diverge areas and understanding impacts of the factors would be beneficial in improving the safety performance of freeway off-ramps. These factors may include driver characteristics, roadway geometric design, environmental and traffic conditions, and vehicle features.

Several studies have been conducted to examine safety performance related to freeway diverge areas and off-ramps. In 1998, Bared et al. (*1*) developed Poisson regression models to estimate the crash frequency for deceleration lanes and the entire ramp as a function of ramp annual average daily traffic (AADT), main-line freeway AADT, deceleration lane length, and ramp configuration. They found that longer deceleration lanes are beneficial in reducing crash frequency. Later, Sarhan et al. (*2*) designed an approach to help achieve optimum predictive models that are related to the length of acceleration and deceleration lanes on the basis of expected collision frequency. The major conclusions were as follows: (*a*) the number of collisions decreases with increasing length of speed change lanes; (*b*) carrying the full width of a speed change lane to the gore of the following ramp might increase the number of collisions on the segment between these two ramps; and (*c*) in cases that warrant an increase or decrease in the basic number of lanes to satisfy the capacity needs of the freeway, a change in the number of lanes should be implemented within the basic section and away from the influence of speed change lanes. Garcia and Romero (*3*) analyzed various deceleration lengths as functions of exit trajectory types, speeds, and localization. They concluded that the length that balances the effects on the main road with the best functionality and safety of the deceleration lane is the one that allows the two maneuvers (a lane change maneuver with a gear deceleration followed by a braking deceleration) to be properly sequenced. Abdel-Aty et al. (*4*) tested various speed limits to evaluate the safety improvement on a section of I-4 in Orlando, Florida. The study makes it clear that speed limits have specific effects on collisions from upstream to downstream of diverge areas on the freeways. Cassidy et al. (*5*) noticed the problem that queues from the segment's off-ramp frequently spill over and occupy its mandatory exit lane. The situation delayed the main-line vehicles as well and would increase weaving conflicts. Janson et al. (*6*) examined the relationship between ramp designs and truck accident rates in Washington State and made a comparison on the basis of limited data from Colorado and California. The results showed that loop ramps in particular have generally higher accident rates, particularly rollovers. In 2008, Chen et al. (*7*) compared crash frequency, crash rate, and crash severity among different exit ramp types (Figure 1): single-lane exit ramps (Type I), single-lane exit ramps without a taper (Type II), two-lane exit ramps with an optional lane (Type III), and two-lane exit ramps without an optional lane (Type IV). A crash prediction model was developed to identify factors contributing to the crash and to quantify the safety impacts of different freeway exit ramps. The crash data analysis results suggested that the Type I exit ramp has the best safety performance in terms of crash frequency and crash rate.

A number of previous studies focused on modeling the injury severity of traffic crashes. In general, injury severity describing the most serious injury to any person involved in a crash can be categorized into levels in an ascending order. Because injury severity is an inherently ordinal variable, ordered multiple choice regressions were widely used to fit injury severity data. O'Donnell and Connor (*8*) used two econometric models [the ordered logit model and the ordered probit model (OPM)] to estimate the linkages between 11 road attributes and the probabilities of sustaining four different levels of injury. They found that increases in the age of the victim and vehicle speed lead to slight

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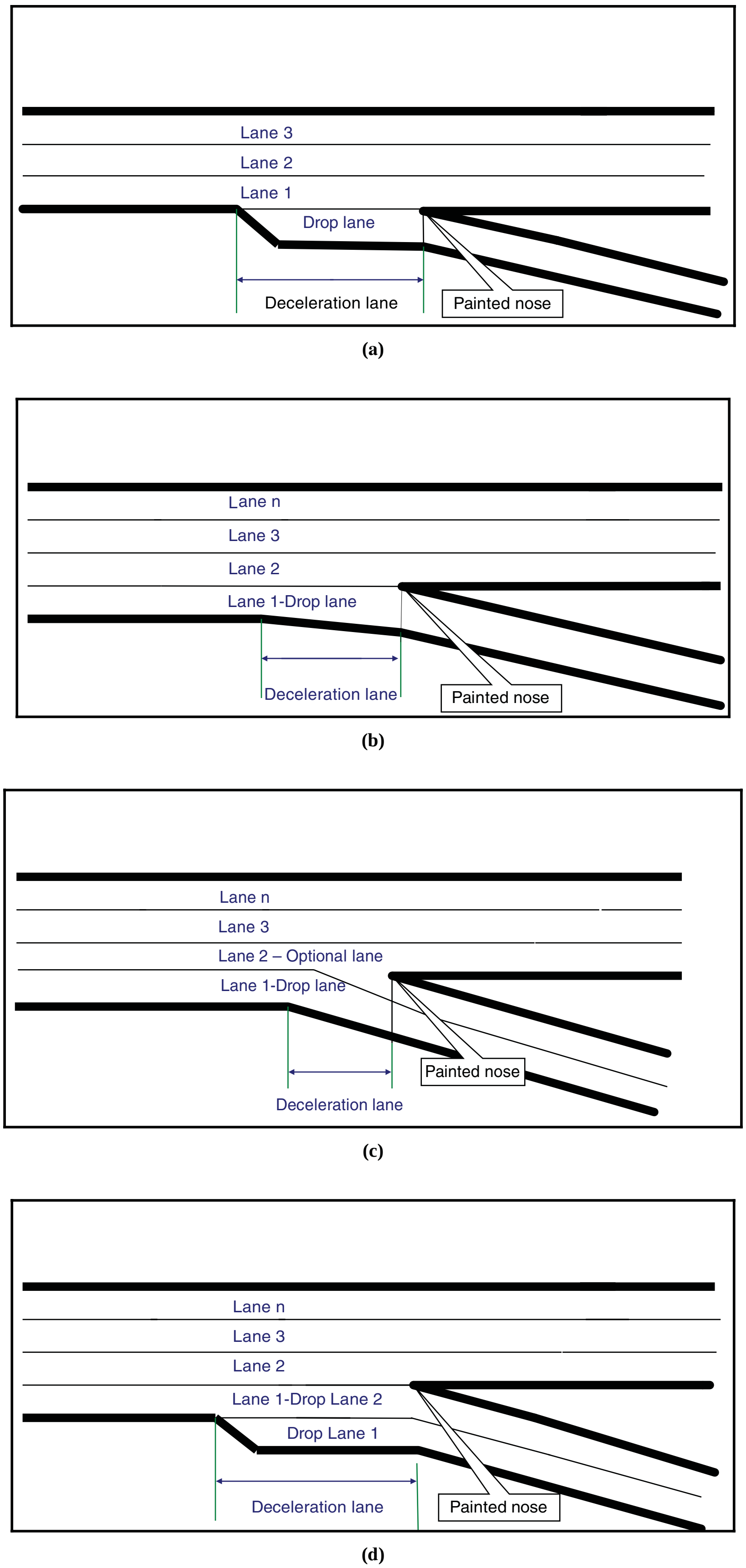

FIGURE 1 Types of exit ramps: (*a*) Type I, parallel from a tangent single-lane exit ramp; (*b*) Type II, single-lane exit ramp without a taper; (*c*) Type III, two-lane exit ramp with an optional lane; and (*d*) Type IV, two-lane exit ramp without an optional lane.

increases in the probabilities of serious injury and death. Other factors contributing to the probabilities of different types of injury include seating position, blood alcohol level, vehicle type, vehicle make, and type of collision. Zajac and Ivan (*9*) adopted the OPM to evaluate the effect of roadway- and area-type features on the injury severity of pedestrian crashes in rural Connecticut. Variables that significantly influence pedestrian injury severity are clear road width, vehicle type, driver and pedestrian alcohol involvement, and pedestrian age 65 years or older. Kockelman and Kweon (*10*) examined the risk of different injury levels sustained under all crash types, two-vehicle crashes, and single-vehicle crashes by using the OPMs. The results suggested that pickups and SUVs are less safe than passenger cars under single-vehicle crash conditions. In two-vehicle crashes, however, these vehicle types are associated with more severe injuries for their drivers and occupants of their collision partners. The results also indicated that males and younger drivers in newer vehicles at lower speeds sustain less severe injuries. Abdel-Aty and Keller (*11*) applied the OPM to explore factors that contribute to injuries at signalized intersections. Tree-based regression has also been adopted to explore the factors that affect each severity level. The probit model results showed that having a divided minor roadway or a higher speed limit on the minor roadway decreased the level of injury, while crashes involving a pedestrian or bicyclist and left-turn crashes had the highest probability of a more severe crash. The results of tree-based models showed a difference in the significant factors that affect the various severity types. Abdel-Aty (*12*) compared the OPM, the multinomial logit model, and the nested logit model for roadway sections, signalized intersections, and toll plazas. The study concluded that the OPM is simple and produces better results than the multinomial model; meanwhile, the nested logit model has almost no effect on the estimation accuracy in comparison with the OPM, given the complexity in identifying the nesting structure.

Other modeling approaches were used in fitting injury severity data in addition to the ordered probit and logit models. The multinomial logit approach was applied to develop the injury severity model by Shankar and Mannering (*13*), Carson and Mannering (*14*), and Ulfarsson and Mannering (*15*). In addition, Yamamoto and Shankar (*16*) developed a bivariate ordered-response probit model of the driver's and most severely injured passenger's severity in collisions with fixed objects. The results of the empirical analysis revealed the effects of drivers' characteristics, vehicle attributes, types of objects, and environmental conditions on both driver and passenger injury severity, and their injury severities have different elasticities with respect to some of the risk factors. Xie et al. (*17*) compared the Bayesian OPM and the traditional OPM. They found that when the sample data size is small, with proper prior setting, the Bayesian model can produce more reasonable parameter estimations and better prediction performance. Das et al. (*18*) adopted the simultaneous estimation approach to examine the effect of a gradual change in intersection influence distance on crash characteristics that explain injury severity in arterial crashes. The partial proportional odds model (PPOM), which allows some but not all slope coefficients to differ across levels of the ordered response, was used by Wang and Abdel-Aty (*19*) to investigate the injury severity of the total and specific left-turn crashes. Results showed that the PPOMs consistently perform better than OPMs.

In summary, numerous studies have analyzed crash injury severity on the basis of various modeling approaches. Studies that examine crash characteristics at freeway diverge areas are also available. However, no study focuses on modeling crash injury severity at freeway diverge areas. In addition, no clear guidelines, neither federal nor state, are available in selecting the optimal exit ramp type to improve the safety performance of freeways (*7*).

The primary objective of this study is to identify factors that contribute to injury severity at freeway diverge areas and especially to investigate the impact of exit ramp types. On the basis of crash data collected at selected freeway exit segments in Florida, the PPOM was adopted to explore the factors, since this approach is less restrictive than the ordered multiple choice approaches. As a comparison, the OPM, the most popular statistical approach for modeling crash injury severity, was also estimated on the basis of the data set.

DATA PREPARATION

In this study, crash data were collected at selected freeway exit ramp segments in Florida. A freeway exit ramp segment, defined as a section of freeway that contains a deceleration lane and an exit ramp, can be divided into two subsegments: (*a*) a 1,500-ft section located upstream of the painted nose and (*b*) a 1,000-ft section located downstream of the painted nose. Thus, a 2,500-ft section was selected to cover the influence area of exit ramps (*7*).

In total, 231 freeway exit segments with different exit ramp types were selected by reviewing aerial photographs of freeway exit ramps in Florida. The milepost of the painted nose for each of the selected segments was obtained from the straight-line diagram provided by the Florida Department of Transportation (FDOT). On the basis of the milepost, crashes within the influence sections were extracted from the Crash Analysis Reporting System maintained by FDOT. As a result, a total of 10,946 crash records were obtained over the period 2003 to 2006. A description of selected variables for the development of injury severity models is given in Table 1. The response variable is an ordered variable with five levels, ranked from the lowest to the highest, representing injury severity. The explanatory variables can be classified into four categories: roadway design, driver, environment and traffic, and crash.

Four exit ramp types widely used in Florida were picked to examine their impacts on crash injury severity. Each type is defined below and illustrated in Figure 1.

- Type I is a full-width parallel from tangent that leads to either a tangent or flat exiting curve that includes a decelerating taper. The horizontal and vertical alignments of Type I exit ramps were based on the selected design speed being equal to or less than that of the intersecting roadways.
- In Type II, the outer lane becomes a drop lane at the exit gore, forming a lane reduction. A paved and striped area beyond the theoretical gore was present at this type of exit ramp to provide a maneuver and recovery area.
- Type III includes two exit lanes; a large percentage of traffic volume on the freeway beyond the painted nose would leave at this type of exit. An auxiliary lane to develop the full capacity of the two-lane exit was developed for 1,500 ft. The entire operation in this type of exit ramp took place over a significant length of the freeway in most cases.
- Type IV is used where one of the through lanes, the outer lane, is reduced and another full-width parallel from a tangent lane developed with a taper is also forced to exit.

METHODOLOGY

Ordered Probit Model

Injury severity, defined as the most severe injury sustained by a person involved in a crash, is a typical ordinal categorical variable that

TABLE 1 Description of Selected Variables for Model Development

Category	Variable	Description	Type	Frequency	Percent
Response	Injury severity	1 (no injury)	Ordinal	5,693	52.0
		2 (possible/invisible injury)		3,046	27.8
		3 (nonincapacitating injury)		1,546	14.1
		4 (incapacitating injury)		597	5.5
		5 (fatal injury)		64	0.6
Road design	Type1	1 (Exit Type I)	Dummy	4,438	40.5
	Type2	1 (Exit Type II)		2,184	20.0
	Type3	1 (Exit Type III)		941	8.6
	Type4	1 (Exit Type IV)		3,383	30.9
	MainLanes	Number of lanes at main line	Count	—	—
	RampLanes	Number of lanes on exit ramps	Count	—	—
	DeLength	Length of deceleration lanes (ft)	Continuous	—	—
	RaLength	Length of entire exit ramp (ft)	Continuous	—	—
	Curve	1 (curve line) 0 (straight)	Binary	436	4
	Grade	1 (down- or upgrade) 0 (level)	Binary	2,136	19.5
	SurfaceType	1 (blacktop) 0 (others)	Binary	8,187	74.8
	ShoulderType	1 (paved) 0 (others)	Binary	8,482	77
	ShoulderWidth	Right shoulder width (ft)	Continuous	—	—
	MainSpeed	Posted speed limit on main line (mi/h)	Continuous	—	—
	SpeedDiff	Difference of posted speed limit between main line and exit ramps (mi/h)	Continuous	—	—
Environment and traffic	Light	1 (daylight) 0 (others)	Binary	7,531	68.8
	Weather	1 (clear) 0 (others)	Binary	7,313	66.8
	Surface	1 (wet) 0 (dry)	Binary	1,809	16.5
	LandType	1 (business) 0 (residential)	Binary	6,313	57.7
	MainADT	ADT per year in thousands at main line	Continuous	—	—
	RampADT	ADT per year in thousands on exit ramps	Continuous	—	—
	PeakHour	1 (off-peak) 0 (peak)	Binary	7,385	67.5
Driver	Age	1 (>64) 0 (≤64)	Binary	378	3.5
	ALCDrug	1 (alcohol/drug involved) 0 (no)	Binary	478	4.4
Crash	HVInv	1 (heavy vehicle involved) 0 (no)	Binary	1,222	11.2
	RearEnd	1 (rear-end crash)	Dummy	5,429	49.6
	Sideswip	1 (sideswipe crash)		1,685	15.4
	Angle	1 (angle crash)		891	8.1

could be scaled into five levels in ascending order. In statistics, the OPM is widely used for fitting the data structure of an ordinal response variable, such as injury severity.

Let Y_i denote the injury severity for the ith observed crash. The OPM can be written as

$$\begin{aligned} &\Pr(Y_i = 1) = \Phi(\tau_1 - \mathbf{x}_i\boldsymbol{\beta}) \\ &\Pr(Y_i = j) = \Phi(\tau_j - \mathbf{x}_i\boldsymbol{\beta}) - \Phi(\tau_{j-1} - \mathbf{x}_i\boldsymbol{\beta}) \qquad j = 2, \dots, J-1 \\ &\Pr(Y_i = J) = 1 - \Phi(\tau_{J-1} - \mathbf{x}_i\boldsymbol{\beta}) \end{aligned} \tag{1}$$

where

- $\Pr(Y_i)$ = probability of the response variable Y_i adopting a specific severity level j (in this case, $J = 5$);
- τ_j = threshold parameter (cutoff points) to be estimated satisfying the restriction $\tau_1 < \tau_2 < \cdots < \tau_{J-1}$;
- $\mathbf{x}_i$ = vector containing the values of observed crash i on the full set of explanatory variables;
- $\boldsymbol{\beta}$ = vector of coefficients associated with the explanatory variables; and
- $\Phi(\,)$ = cumulative distribution function of the standard normal distribution.

The OPM can also be rewritten in terms of the cumulative probability that an outcome is less than or equal to m in the following equivalent ways:

$$\begin{aligned} &\Pr(Y_i \le m) = \sum_{j=1}^{m} \Pr(Y_i = j) = \Phi(\tau_j - \mathbf{x}_i\boldsymbol{\beta}) \\ &\Pr(Y_i > m) = 1 - \Pr(Y_i \le m) = 1 - \Phi(\tau_j - \mathbf{x}_i\boldsymbol{\beta}) \end{aligned} \tag{2}$$

From Equation 1 or 2, the slope coefficients $\boldsymbol{\beta}$ are the same across the injury severity levels while the cutoff points differ; in other words, $\boldsymbol{\beta}$ is independent of the injury severity level (j) for the OPM. The identification of slope coefficients is an important assumption of the OPM, called the parallel regression assumption (*20*). However, a key problem of the OPM is that its assumptions are always violated; it is common for one or more coefficients to differ over the outcome levels (*20–22*).

A Wald test proposed by Brant in 1990 allows both an overall test that all $\boldsymbol{\beta}_j$ are equal and tests of the equality of individual coefficients by comparing slope coefficients of the $J-1$ binary logit models implied by the ordered regression model. The "brant" command in the STATA software package was used to perform the Wald test. If the probability of the test (p-value) is less than a critical value (usually .05), the hypothesis that slope coefficients remain identical across the response values is rejected; in other words, there is strong evidence that the slope coefficients violate the assumption.

Partial Proportional Odds Model

As mentioned above, the OPM is always overly restricted when its parallel regression assumption is violated. To relax the restriction, the PPOM was proposed by Peterson and Harrell (*22*). In the PPOM, some of the slope coefficients can be identical for all outcome values if the parallel regression assumptions are not violated; other coefficients can be different if their assumptions are violated. The cumulative probability equation is given as the following:

$$\Pr\left(Y_i > j \middle| \mathbf{x}_i\right) = \frac{\exp\left(\alpha_j + \mathbf{x}_i^a \boldsymbol{\beta}^a + \mathbf{x}_i^n \boldsymbol{\beta}_j^n\right)}{1 + \exp\left(\alpha_j + \mathbf{x}_i^a \boldsymbol{\beta}^a + \mathbf{x}_i^n \boldsymbol{\beta}_j^n\right)} \qquad j = 1, 2, \ldots, J-1 \tag{3}$$

where

- α_j = jth constant coefficient (equal to the negatives of the cutoff points);
- $\mathbf{x}_i^a$ = vector containing the values of observation i on that subset of explanatory variables for which the parallel assumptions are not violated;
- $\boldsymbol{\beta}^a$ = vector of coefficients associated with the nonviolated variables, the same across values of Y;
- $\mathbf{x}_i^n$ = vector containing the values of observation i on that subset of explanatory variables for which the parallel assumptions are violated; and
- $\boldsymbol{\beta}_j^n$ = vector of coefficients associated with the violated variables, differing across the response values.

The values of constant coefficients and regression coefficients are estimated by the maximum likelihood estimation method.

The PPOM is often interpreted in terms of odds ratios for cumulative probabilities. The odds are given as follows:

$$\frac{\Pr\left(Y > j \middle| \mathbf{x}\right)}{\Pr\left(Y \le j \middle| \mathbf{x}\right)} = \exp\left(\alpha_j + \mathbf{x}\boldsymbol{\beta}_j\right) \tag{4}$$

The sign of the slope coefficient determines the directional change of the probability. A positive slope coefficient means that an increase of the associated variable tends to raise the probability of $Y > j$, if all other variables are held constant, while a negative slope value indicates that the increase is more likely to reduce the probability of $Y > j$.

Another useful approach in interpreting the coefficients is the marginal effects, commonly defined as the slope of the probability curve relating x_k to $\Pr(Y = j|X)$ at the mean values of all variables, with all other explanatory variables held constant.

$$\begin{aligned}\frac{\partial \Pr\left(y = j\right)}{\partial x_k} &= \frac{\partial F\left(\tau_j - \bar{\mathbf{x}}\boldsymbol{\beta}_j\right)}{\partial x_k} - \frac{\partial F\left(\tau_{j-1} - \bar{\mathbf{x}}\boldsymbol{\beta}_{j-1}\right)}{\partial x_k} \\ &= \beta_{k,j}\left[f\left(\tau_{j-1} - \bar{\mathbf{x}}\boldsymbol{\beta}_{j-1}\right) - f\left(\tau_j - \bar{\mathbf{x}}\boldsymbol{\beta}_j\right)\right]\end{aligned} \tag{5}$$

where

- $F(\,)$ = cumulative distribution function for logistic distributed variables;
- $f(\,)$ = probability density function for logistic distributed variables;
- $\bar{\mathbf{x}}$ = mean values of all variables; and
- $\beta_{k,j}$ = slope coefficient of the kth variable for the jth outcome level.

For continuous variables, the marginal effects are calculated as the derivative of the curve; for dummy or binary independent variables, the marginal effects are computed as the difference of probabilities due to the discrete change in the variables from 0 to 1.

For assessing the goodness of fit of the models, pseudo-R^2, Akaike's information criterion (AIC), and the Bayesian information criterion (BIC) were provided in the STATA package. If the unconstrained model (with all slope coefficients) does much better than the constrained model (constant coefficients only), pseudo-R^2 is closer to 1. The model with the smaller AIC is considered the better-fitting model. In addition, if the difference of BIC values between two models ($\text{BIC}_{\text{Model 1}} - \text{BIC}_{\text{Model 2}}$) is less than 0, Model 1 is preferred. If the difference is greater than 0, Model 2 is preferred (*21*).

ESTIMATION RESULTS

Ordered Probit Model

The OPM was estimated with the command "oprobit" in the STATA software package. The stepwise method was applied to select the explanatory variables that have significant contributions to the outcome probabilities from the initial variable list (Table 1) with a confidence level of 90%. The fitted OPM is given in Table 2.

Nine variables found to be statistically nonsignificant were excluded from the model. These variables include exit ramp types (Types I, II, III, and IV), number of lanes on ramp, road surface type, shoulder type, speed limit difference between main line and ramps, average daily traffic (ADT) on ramps, drivers' age, rear-end crash, and angle crash. It can be concluded that these variables have no significant effects on injury severity at freeway diverge areas.

In total, 17 variables were included in the fitted model. The slope coefficient of the variable MainLanes is positive, implying that the presence of more lanes on the main line tends to increase the probability of more severe crash injuries at freeway diverge areas. A longer deceleration lane on the diverge areas is more likely to decrease the injury severity (coefficient = –0.001), while the length of ramps has the reverse impact (coefficient = 0.001). A crash occurring at a diverge area with curved alignments or down- or upgrades is expected to result in more severe injury because of their negative coefficients. According to the slope coefficients, it also can be concluded that good light conditions, good weather conditions, and diverge areas located in business zones tend to decrease the probability of severe injuries, while a large ADT on main lines increases the probability of severe injuries. Two factors, alcohol or drug involvement and hit against barriers, are highly significant in causing a severe injury at diverge areas. In addition, sideswiping crashes are less likely to increase injury severity. Severe crashes are more likely to occur during the off-peak period.

TABLE 2 OPM Estimation

Explanatory Variable	Coefficient	Standard Error	z	$p > \|z\|$	95% Confidence Interval Lower Bound	Upper Bound
MainLanes	0.0553	0.0141	3.9400	0.0000	0.0278	0.0829
DeLength	–0.0001	0.0001	–1.7800	0.0750	–0.0003	0.0000
RaLength	0.0001	0.0000	5.6600	0.0000	0.0000	0.0001
Curve	0.2157	0.0555	3.8900	0.0000	0.1070	0.3245
Grade	0.0813	0.0280	2.9000	0.0040	0.0264	0.1362
ShoulderWidth	0.0159	0.0060	2.6400	0.0080	0.0041	0.0277
MainSpeed	–0.0062	0.0022	–2.8400	0.0050	–0.0105	–0.0019
Light	–0.0766	0.0252	–3.0400	0.0020	–0.1259	–0.0272
Weather	–0.1193	0.0287	–4.1600	0.0000	–0.1756	–0.0631
Surface	–0.0833	0.0365	–2.2800	0.0220	–0.1549	–0.0118
LandType	–0.0745	0.0232	–3.2100	0.0010	–0.1200	–0.0289
MainADT	0.0006	0.0002	2.8000	0.0050	0.0002	0.0010
PeakHour	0.1025	0.0247	4.1500	0.0000	0.0541	0.1510
ALCDrug	0.4722	0.0525	8.9900	0.0000	0.3692	0.5751
HVInv	–0.2072	0.0377	–5.5000	0.0000	–0.2810	–0.1333
Sideswip	–0.5452	0.0339	–16.0600	0.0000	–0.6117	–0.4787
Barrier	0.1970	0.0461	4.2800	0.0000	0.1068	0.2873
/cut1	0.0955	0.1356			–0.1704	0.3613
/cut2	0.9119	0.1358			0.6457	1.1781
/cut3	1.6459	0.1367			1.3780	1.9137
/cut4	2.6579	0.1431			2.3775	2.9383

NOTE: AIC = 24,767.96; BIC = 24,921.27; pseudo-R^2 = 0.0273; number of observations = 10,946; likelihood ratio chi-square (11) = 693.3; Prob > chi-square = 0.0000; log likelihood = –12,362.978.

Some results are counterintuitive. The probability of severe injuries decreases with an increase in the posted limit on main lines since the slope coefficient is negative. A possible explanation was given in the previous research (*7*). A wet road surface also is more likely to reduce injury severity. A possible reason for this phenomenon is that drivers pay more attention on a rainy day. The other two factors are heavy-vehicle involvement (coefficient = –0.2072) and shoulder width (coefficient = 0.0159).

The results of Brant tests, which examine the violation of the parallel regression assumption, are given in Table 3. From the table, there is strong evidence for rejecting the parallel regression assumption for the independent variables MainLanes, RaLength, MainSpeed, Weather, LandType, PeakHour, ALCDrug, HVInv, and Sideswip (p-values < .05). Thus, these variables should differ across injury severity levels. Other variables, including DeLength, Curve, Grade, ShoulderWidth, Light, Surface, MainADT, and Barrier, do not violate the assumption and should remain the same across injury severity levels.

TABLE 3 Parallel-Lines Assumption Test (Brant Test)

Variable	Chi-Square	p-Value	DF
All	372.26	0	51
MainLanes	45.8100	0.0000	3
DeLength	2.2500	0.5230	3
RaLength	9.5000	0.0230	3
Curve	4.1000	0.2510	3
Grade	5.2200	0.1560	3
ShoulderWidth	3.5000	0.3200	3
MainSpeed	33.8800	0.0000	3
Light	5.0900	0.1650	3
Weather	21.9700	0.0000	3
Surface	6.2800	0.0990	3
LandType	17.7000	0.0010	3
MainADT	5.9900	0.1120	3
PeakHour	22.7600	0.0000	3
ALCDrug	30.8100	0.0000	3
HVInv	18.3500	0.0000	3
Sideswip	20.7700	0.0000	3
Barrier	4.9900	0.1720	3

Partial Proportional Odds Model

To relax the restrictions on the explanatory variables that violated the parallel regression assumption in the OPM, coefficients of all selected variables in the OPM were reestimated with the command "gologit2" in the STATA package. The fitted PPOM is given in Table 4, and the marginal effects calculated with the command "mfx2" are given in Table 5. From Tables 2 and 4, the pseudo-R^2 of

TABLE 4 PPOM Estimation

Variable	Coefficient	Standard Error	z	$p > \|z\|$	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
$j = 1$						
MainLanes	0.1662	0.0245	6.7700	0.0000	0.1181	0.2143
DeLength	–0.0002	0.0001	–1.8700	0.0610	–0.0005	0.0000
RaLength	0.0001	0.0000	5.1500	0.0000	0.0001	0.0002
Curve	0.3685	0.0940	3.9200	0.0000	0.1841	0.5528
Grade	0.1422	0.0474	3.0000	0.0030	0.0493	0.2351
ShoulderWidth	0.0277	0.0101	2.7300	0.0060	0.0078	0.0476
MainSpeed	–0.0192	0.0039	–4.8600	0.0000	–0.0269	–0.0115
Light	–0.1281	0.0426	–3.0100	0.0030	–0.2117	–0.0446
Weather	–0.2723	0.0511	–5.3300	0.0000	–0.3725	–0.1721
Surface	–0.1527	0.0619	–2.4700	0.0140	–0.2740	–0.0314
LandType	–0.1680	0.0417	–4.0300	0.0000	–0.2497	–0.0862
MainADT	0.0010	0.0003	3.0100	0.0030	0.0004	0.0017
PeakHour	0.0933	0.0439	2.1200	0.0340	0.0072	0.1794
ALCDrug	0.6022	0.1008	5.9700	0.0000	0.4046	0.7998
HVInv	–0.4529	0.0671	–6.7500	0.0000	–0.5845	–0.3214
Sideswip	–0.9967	0.0606	–16.4400	0.0000	–1.1155	–0.8778
Barrier	0.3551	0.0779	4.5600	0.0000	0.2024	0.5078
Cons	0.1839	0.2419	0.7600	0.4470	–0.2902	0.6580
$j = 2$						
MainLanes	–0.0191	0.0278	–0.6900	0.4910	–0.0735	0.0353
DeLength	–0.0002	0.0001	–1.8700	0.0610	–0.0005	0.0000
RaLength	0.0001	0.0000	5.0800	0.0000	0.0001	0.0002
Curve	0.3685	0.0940	3.9200	0.0000	0.1841	0.5528
Grade	0.1422	0.0474	3.0000	0.0030	0.0493	0.2351
ShoulderWidth	0.0277	0.0101	2.7300	0.0060	0.0078	0.0476
MainSpeed	0.0007	0.0046	0.1500	0.8770	–0.0083	0.0097
Light	–0.1281	0.0426	–3.0100	0.0030	–0.2117	–0.0446
Weather	–0.1583	0.0582	–2.7200	0.0070	–0.2724	–0.0442
Surface	–0.1527	0.0619	–2.4700	0.0140	–0.2740	–0.0314
LandType	–0.0143	0.0504	–0.2800	0.7770	–0.1131	0.0845
MainADT	0.0010	0.0003	3.0100	0.0030	0.0004	0.0017
PeakHour	0.2860	0.0557	5.1400	0.0000	0.1769	0.3952
ALCDrug	0.6998	0.1005	6.9600	0.0000	0.5028	0.8967
HVInv	–0.1956	0.0844	–2.3200	0.0200	–0.3609	–0.0303
Sideswip	–0.7525	0.0809	–9.3000	0.0000	–0.9111	–0.5940
Barrier	0.3551	0.0779	4.5600	0.0000	0.2024	0.5078
Cons	–1.9195	0.2807	–6.8400	0.0000	–2.4697	–1.3693
$j = 3$						
MainLanes	–0.0805	0.0425	–1.8900	0.0590	–0.1638	0.0029
DeLength	–0.0002	0.0001	–1.8700	0.0610	–0.0005	0.0000
RaLength	0.0001	0.0000	2.1600	0.0310	0.0000	0.0002
Curve	0.3685	0.0940	3.9200	0.0000	0.1841	0.5528
Grade	0.1422	0.0474	3.0000	0.0030	0.0493	0.2351
ShoulderWidth	0.0277	0.0101	2.7300	0.0060	0.0078	0.0476
MainSpeed	0.0114	0.0075	1.5300	0.1270	–0.0032	0.0260
Light	–0.1281	0.0426	–3.0100	0.0030	–0.2117	–0.0446
Weather	0.0978	0.0919	1.0600	0.2870	–0.0824	0.2780
Surface	–0.1527	0.0619	–2.4700	0.0140	–0.2740	–0.0314
LandType	–0.1270	0.0831	–1.5300	0.1270	–0.2899	0.0359

(continued on next page)

TABLE 4 *(continued)* **PPOM Estimation**

Variable	Coefficient	Standard Error	z	$p > \|z\|$	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
MainADT	0.0010	0.0003	3.0100	0.0030	0.0004	0.0017
PeakHour	0.3823	0.0977	3.9100	0.0000	0.1908	0.5738
ALCDrug	1.0788	0.1303	8.2800	0.0000	0.8234	1.3342
HVInv	–0.1465	0.1433	–1.0200	0.3070	–0.4275	0.1344
Sideswip	–0.7868	0.1457	–5.4000	0.0000	–1.0723	–0.5012
Barrier	0.3551	0.0779	4.5600	0.0000	0.2024	0.5078
Cons	–3.8446	0.4477	–8.5900	0.0000	–4.7222	–2.9670
$j = 4$						
MainLanes	–0.0100	0.1187	–0.0800	0.9330	–0.2426	0.2226
DeLength	–0.0002	0.0001	–1.8700	0.0610	–0.0005	0.0000
RaLength	0.0003	0.0001	3.6100	0.0000	0.0001	0.0005
Curve	0.3685	0.0940	3.9200	0.0000	0.1841	0.5528
Grade	0.1422	0.0474	3.0000	0.0030	0.0493	0.2351
ShoulderWidth	0.0277	0.0101	2.7300	0.0060	0.0078	0.0476
MainSpeed	–0.0092	0.0221	–0.4200	0.6780	–0.0525	0.0342
Light	–0.1281	0.0426	–3.0100	0.0030	–0.2117	–0.0446
Weather	–0.6077	0.2452	–2.4800	0.0130	–1.0883	–0.1271
Surface	–0.1527	0.0619	–2.4700	0.0140	–0.2740	–0.0314
LandType	0.3086	0.2828	1.0900	0.2750	–0.2456	0.8627
MainADT	0.0010	0.0003	3.0100	0.0030	0.0004	0.0017
PeakHour	2.1912	0.7248	3.0200	0.0030	0.7707	3.6118
ALCDrug	2.2798	0.2614	8.7200	0.0000	1.7674	2.7921
HVInv	0.2302	0.3941	0.5800	0.5590	–0.5423	1.0026
Sideswip	–1.3264	0.5872	–2.2600	0.0240	–2.4773	–0.1754
Barrier	0.3551	0.0779	4.5600	0.0000	0.2024	0.5078
Cons	–7.5084	1.4672	–5.1200	0.0000	–10.3841	–4.6327

NOTE: AIC = 24,483.19; BIC = 24,833.63; pseudo-R^2 = 0.0406; number of observations = 10,946; likelihood ratio chi-square (44) = 1,032.06; Prob > chi-square = 0; log likelihood = –12,193.597.

TABLE 5 Marginal Effects for PPOM

Variable	No Injury	Possible Injury	Nonincapacitating Injury	Incapacitating Injury	Fatal Injury
MainLanes	–0.0413590	0.0444260	0.0011127	–0.0040914	–0.0000225
DeLength	0.0000605	–0.0000229	–0.0000253	–0.0000119	–0.0000005
RaLength	–0.0000283	0.0000083	0.0000152	0.0000041	0.0000007
Curve	–0.0920471	0.0284194	0.0415061	0.0209743	0.0009849
Grade	–0.0352547	0.0128040	0.0150396	0.0072280	0.0003337
ShoulderWidth	–0.0070014	0.0026021	0.0029312	0.0013545	0.0000622
MainSpeed	0.0047904	–0.0048974	–0.0004740	0.0006029	–0.0000206
Light	0.0318999	–0.0117578	–0.0134966	–0.0064022	–0.0002949
Weather	0.0679167	–0.0429057	–0.0299870	0.0064612	–0.0015335
Surface	0.0379736	–0.0149488	–0.0155553	–0.0071379	–0.0003262
LandType	0.0418779	–0.0396778	0.0043014	–0.0072325	0.0006794
MainADT	–0.0002615	0.0000980	0.0001095	0.0000510	0.0000023
PeakHour	–0.0232604	–0.0198961	0.0246688	0.0144232	0.0040660
ALCDrug	–0.1483914	0.0183007	0.0434554	0.0689433	0.0175296
HVInv	0.1107874	–0.0817382	–0.0218906	–0.0076910	0.0005662
Sideswip	0.2334285	–0.1341840	–0.0671942	–0.0300329	–0.0020251
Barrier	–0.0882881	0.0278545	0.0395886	0.0199980	0.0009374

the PPOM is .0406, greater than that of the OPM (.0273). Therefore, it can be concluded that the PPOM was much better than the OPM in fitting the observations. In addition, the AIC in the PPOM (24,483.19) is smaller than that in the OPM, and the difference between the BIC of the PPOM (24,833.63) and that of the OPM (24,921.27) is less than 0. The two comparisons also validate the conclusion of the goodness of fit.

The variable of the number of lanes on the main line (MainLanes) violates the parallel regression assumption, so its coefficients differ across injury severity levels (Table 4). The sign of the coefficient for $j = 1$ is positive, implying that an increase in the number of lanes on the main line is more likely to increase the probability of injury than the probability of noninjury. However, the sign of the coefficient for $j = 3$ is negative, indicating that the factor tends to decrease the probability of severe injury (incapacitating injury and fatal injury). The coefficients for $j = 2$ and $j = 4$ are not statistically significant (p-values >> .1). The impacts were also confirmed in Table 5. The marginal effects (Table 5) illustrate that the probabilities of possible injury and nonincapacitating injury will increase with an increase in the number of lanes on the main line, while the probabilities of noninjury and incapacitating injury will decrease. The probability of fatal injury is not sensitive to the increase in lanes on the main line since its marginal effect is small (−0.0000225).

The assumption is also violated for the factor of the length of ramps (RaLength). From Table 4, the coefficients for $j = 1$, 2, 3, and 4 are positive and different. On the basis of the sign of coefficients, it can be concluded that an increase in ramp length is more likely to increase injury severity. The conclusion can also be derived from the marginal effects: the probability of noninjury decreases with an increase in the length of ramps, while the probabilities of the four injury levels are raised.

The posted speed limit on main line, another violated variable, is likely to increase the probability of noninjury on the basis of the sign of the coefficient for $j = 1$; the other coefficients are not significant. According to the marginal effects, the probability of noninjury increases with a high speed limit.

The coefficients of weather conditions are all negative except for $j = 3$ (where p-value = .287 > .1). This means that good weather conditions tend to decrease injury severity. From the marginal effects, it is known that the probability of noninjury increases when weather conditions change from bad (= 0) to good (= 1). The probabilities of possible injury, nonincapacitating injury, and fatal injury decrease in the same situation.

The coefficients of land type differ across injury severity levels. The coefficient for $j = 1$ is significant and negative, while the others are nonsignificant. In addition, the marginal effect for $j = 1$ is positive. It can be concluded that business zones tend to increase the probability of noninjury rather than injury.

Off-peak period has strong positive effects on the probability of severe injury since its coefficients are all positive and the coefficient values increase with increasing injury severity level. In other words, severe injuries readily occur in off-peak periods. This conclusion can also be derived from Table 5.

Alcohol or drug involvement is more likely to increase injury severity since its coefficients are all positive and significant. The coefficient for fatality is especially big (2.2798). Thus, alcohol or drug involvement has a strong effect on the probability of severe injuries.

The coefficients of heavy-vehicle involvement for $j = 1$ and $j = 2$ are significant and negative. Marginal effects for the two levels are 0.1107874 and −0.0817382, respectively. The conclusion is that heavy-vehicle involvement is more likely to increase the probability of noninjury rather than injury severity.

On the basis of the coefficients and the marginal effects of the dummy variable, it is known that crash type has different effects on injury severity. Sideswiping crashes are more likely to result in a decrease in the probability of severe injuries, but with different slopes. Hitting a concrete barrier tends to increase the injury severity at the slopes.

For the variables that do not violate the parallel regression assumption, such as DeLength, Curve, Grade, ShoulderWidth, Light, and Surface, all coefficients keep constant across injury severity levels in the PPOM. Thus, the interpretations of these variables in the PPOM are similar to those in the OPM.

SUMMARY AND CONCLUSIONS

This study evaluated the impacts of various factors (including exit ramp type, geometric design features, environmental and traffic characteristics, and driver and crash characteristics) on injury severity at freeway diverge areas. Two injury severity prediction models were developed to identify factors that contribute to injury severity at freeway diverge areas with the partial proportional odds technology and ordered probit regression. The PPOM, which allows one or more slope coefficients to differ across severity levels, is much better than the OPM in fitting crash injury severity data. The interpretations of coefficients violating the assumption in the PPOM are often different from those in the OPM. On the basis of the prediction model, the following conclusions can be drawn:

- The length of deceleration lanes is a significant factor affecting injury severity. Longer deceleration lanes are more likely to reduce injury severity, while the length of ramps has the reverse impact. Curves and grades at diverge segments are the two significant factors tending to increase injury severity.
- Good light conditions and good weather conditions have great impacts on reducing injury severity at freeway diverge areas.
- Alcohol or drug involvement has great positive effects on injury severity.
- Other significant factors are the number of lanes on the main line, speed limit on the main line, shoulder width, ADT on the main line, surface conditions (wet or dry), land type (business or residential), and heavy-vehicle involvement.
- Exit ramp types (Types I, II, III, and IV) have no significant impacts on injury severity at freeway diverge areas.
- Some road design features, such as the number of ramp lanes, road surface type (blacktop or others), shoulder type, and the difference between the speed limit on the main line and ramps, also do not contribute to injury severity at freeway diverge areas.

This study focused on the safety performance of freeway diverge areas. The impacts on injury severity on the ramps were not considered. Furthermore, the interactions between factors of diverge areas and those of ramps, and even those of connecting roads, need to be analyzed. An injury severity model for ramps and a total severity model should be developed in the future to obtain a better analysis of the impacts of various factors on injury severity of freeway exit ramp areas (both diverge areas and ramps). In addition, collection of more variables will be helpful in refitting the models developed in this study and in providing more reasonable interpretations for some coefficients.

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