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Analysis of driver injury severity levels at multiple locations using ordered probit models

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Abstract

Problem: The occurrence and outcome of traffic crashes have long been recognized as complex events involving interactions between many factors, including the roadway, driver, traffic characteristics, and the environment. This study is concerned with the outcome of the crash. *Method*: Driver injury severity levels are analyzed using the ordered probit modeling methodology. Models were developed for roadway sections, signalized intersections, and toll plazas in Central Florida. All models showed the significance of driver's age, gender, seat belt use, point of impact, speed, and vehicle type on the injury severity level. Other variables were found significant only in specific cases. *Results*: A driver's violation was significant in the case of signalized intersections. Alcohol, lighting conditions, and the existence of a horizontal curve affected the likelihood of injuries in the roadway sections' model. A variable specific to toll plazas, vehicles equipped with Electronic Toll Collection (ETC), had a positive effect on the probability of higher injury severity at toll plazas. Other variables that entered into some of the models were weather condition, area type, and some interaction factors. This study illustrates the similarities and the differences in the factors that affect injury severity between different locations.

Keywords: Injury severity; Signalized intersections; Toll plazas; Roadway sections; Ordered probit

1. Introduction

Traffic safety is a major concern because of the economic and social costs of traffic crashes. According to the national statistics, there were 41,821 fatalities (people lost their lives) in 6,394,000 police-reported motor-vehicle traffic crashes. Also, 3,189,000 people were injured and 4,286,000 crashes involved property damage only. There were 1.5 fatalities for every 100 million-vehicle-miles of total travel in 2000. The injury rate per 100 million vehicle miles of total travel in 2000 was 116. The fatality rate per 100,000 people was 15.23 in 2000, slightly lower than the 1999 rate of 15.30. An average of 115 fatalities occurred each day in traffic crashes in 2000 (or 1 every 13 minutes). Vehicle occupants accounted for 87% of the traffic crashes' fatalities in 2000. Lawrence (1995) reported the results from an analysis of motor-vehicle crash economic costs. Economic cost components include productivity losses, property damage, medical costs, rehabilitation costs, travel delay, legal and court costs, emergency service costs, insurance administration costs, premature funeral costs, and costs to employers. The estimated total economic cost of the U.S. motor-vehicle crashes in 1994 was $150.5 billion.

Elvik (2000) presented estimates of how much traffic crashes cost the national economy for a number of countries including the United States, stated as a percentage of the gross national product. Results showed that on average, the total costs of road crashes (including an economic value of lost quality of life) were estimated at about 2.5% of the gross national product (GNP). Excluding the valuation of lost quality of life, road crash costs on average amounted to 1.3% of the GNP. When valuation of lost quality of life is included, costs ranged from 0.5% to 5.7% of GNP. When valuation of lost quality of life is disregarded, costs ranged from 0.3 to 2.8% of GNP.

Researchers have employed many statistical techniques to analyze driver injury severity. Among these techniques were multinomial logit, nested logit, and ordered logit and probit models. For example, Nassar, Saccomanno, and Shortreed (1994) estimated a nested logit model to predict crash severity. Three separate models were calibrated for three crash situations: single-vehicle, two-vehicle, and

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multi-vehicle crashes. Factors that affect the level of damage experienced by individuals involved in traffic crashes include a crash dynamic term, seating position, seat belt use, vehicle condition, vehicle mass, driver condition, and driver action. Road surface condition was insignificant in the models. Bad weather conditions may prompt drivers to slow down and keep a safe distance from other vehicles.

Shankar and Mannering (1996) used a multinomial logit specification for estimating motorcycle rider crash severity likelihood conditioned on the occurrence of a crash. Five levels of severity are considered: property damage only, possible injury, evident injury, severe injury, and fatality. Crash data were 5-year statewide data on single-vehicle motorcycle crash from the state of Washington. Results showed that the multinomial logit formulation is a promising approach to evaluate the determinants of motorcycle crash severity. Shankar, Mannering, and Barfield (1996) estimated a nested logit model to analyze crash severity of single-vehicle crashes on rural freeways. All possible nesting structures (which examine possible correlation among the choices) were considered and statistically tested by the likelihood ratio test. The authors found that a nested-logit model, which treated property damage only (no injury) and possible shared characteristics of injury crashes, fits the data best.

Chang and Mannering (1999) estimated a nested logit model to study the occupancy crash injury severity relationship. Crash data of principle arterials, state highways, and interstates in Seattle, Washington, during 1994 were used in the analysis. The dependent variable was the crash severity, which represents the most severe level of injury sustained by any vehicle occupant involved in the crash. The occupancy can be significant because vehicles with large occupancies have an increased likelihood of having someone seriously injured. Separate models were estimated for truck-involved crashes and for non-truck-involved crashes. Results showed that increased severity was more likely for truck-involved crashes, high speed limits, crashes occurring when a vehicle is making a right or left turn, and rear-end types of collisions.

Krull, Khattak, and Council (2000) used logit models to analyze driver injury severity involved in a single-vehicle crash. Three-year crash data from Michigan and Illinois were analyzed to explore the effect of rollover, while controlling for roadway, vehicle, and driver factors. Results showed that driver injury severity increases with: (a) failure to use a seatbelt, (b) passenger cars as opposed to pick-up trucks, (c) alcohol use, (d) daylight, (e) rural roads as opposed to urban, (f) posted speed limit, and (g) dry pavement as opposed to slippery pavement.

Hutchinson (1986) developed an ordered probit model to study occupants' injury severity when involved in traffic crashes. British crash data for 1962–1972 had been processed to give a cross-tabulation of the severity of injury to the driver and to the front seat passenger in four types of single-vehicle crashes (overturning and non-overturning, each in rural and urban areas). Results showed that passengers tend to be more seriously injured than drivers in non-overturning, but that there is no difference in overturning crashes.

O'Donnell and Connor (1996) estimated two ordered probit/logit models to predict the severity of traffic crash injuries. Data from New South Wales, Australia, was used to estimate the two models. Results showed that increases in the age of the victim and vehicle speed lead to slight increases in the probabilities of serious injury and death. Other factors that have a similar or greater effect on the probabilities of different types of injury include seating position, blood alcohol level, vehicle type, vehicle make, and type of collision.

Klop (1998) examined the impacts of physical and environmental factors on the severity of injury to bicyclists in North Carolina. Using the ordered probit model, the effect of a set of roadway, environmental, and crash variables on injury severity was explored. Separate models were estimated for rural and urban locations. Results indicated that straight grades, curved grades, darkness, and fog significantly increase injury severity.

Renski, Khattak, and Council (1998) estimated ordered probit models to explore the effects of policy variables on injury severity. Results showed that highway segments where speed limits were raised by 10 mph resulted in a higher probability of increased severity than those raised by only 5 mph. No significant changes in injury severity were found for the highway segments where speed limits were raised from 65 to 70 mph.

Duncan, Khattak, and Council (1999) used ordered probit modeling to examine the occupant characteristics and roadway and environmental conditions that influence injury severity in rear-end crashes involving truck-passenger car collisions. Two models were developed, one with the basic variables and the other including interactions among the independent variables. Results revealed that an increased severity risk exists for higher speed crashes, those occurring at night, for women, when alcohol is involved, and for crashes when a passenger car rear-ends a truck at a large differential speed between the two vehicles.

Khattak (1999) applied the ordered probit model to examine the effect of information (accuracy of information conveyed by brake and turning lights) and other factors on rear-end crash propagation and the propensity of driver injury in such crashes. Results on injury severity showed that in a two-vehicle crash, the leading driver is more likely to be injured, whereas, in a three-vehicle crash, the driver in the middle is likely to be more severely injured. Furthermore, as rear-end crashes propagate from two-vehicles to three-vehicles the last driver is relatively less severely injured.

Toshiyuki and Shankar (2002) used a bivariate ordered-response probit model to study driver and most severely injured passenger severity in collision with fixed objects in Washington State. Results showed that icy roadway surface and rain decrease the probability of more severe driver injury. The type of fixed objects significantly affects driver's injury severity. Guardrails have different effects on driver's injury whether the collisions are with its face or with its leading end. Proper use of a restraint system significantly decreases the probability of more severe driver injury. Male and younger drivers have a lower probability of more severe injury, probably because of their physical strength. Also, driver's unconsciousness causes more severe driver injury.

Many studies applied the ordered probit modeling technique to injury, severity (e.g., O'Donnell & Connor, 1996; Klop, 1998; Renski et al., 1998; Duncan et al., 1999). However, none of these models addressed the injury severity of crashes occurred in the vicinity of toll plazas, or compared the factors that affect injury severity among different highway locations. In this paper, the ordered probit model is used to study injury severity of drivers involved in traffic crashes in the vicinity of toll plazas, at roadway sections, and at signalized intersections.

2. Methodology

Some multinomial variables (e.g., injury severity) are inherently ordered. In these cases, although the outcome is discrete, the multinomial logit models would fail to account for the ordinal nature of the dependent variable. The ordered probit models have come into fairly wide use as a framework for analyzing such responses. The ordered multiple-choice model assumes the relationship:

$$\sum_{j=1}^{j} P_n(j) = F(\alpha_j - \beta_j X_n, \theta),\ j = 1, \ldots, J-1$$

$$P_n(J) = 1 - \sum_{j=1}^{J-1} P_n(j)$$

where $P_n(j)$ is the probability that subject n ($n = 1, \ldots, N$) belongs to category j, α_j is an alterative specific constant, X_n is a vector of measurable characteristics specific to subjects, β_j is a vector of estimable coefficients, and θ is a parameter that controls the shape of probability distribution F. Ordered probit models, which assume standard normal distribution for F are the most commonly used. The ordered probit model has the following form:

$$P_n(1) = \Phi(\alpha_1 - \beta_j X_n)$$

$$P_n(j) = \Phi(\alpha_j - \beta_j X_n) - \Phi(\alpha_{j-1} - \beta_j X_n),\ j = 2, \ldots, j-1$$

$$P_n(J) = 1 - \sum_{j=1}^{J-1} P_n(j)$$

where Φ is the cumulative standard normal distribution function. For all the probabilities to be positive, we must have $\alpha_1 < \alpha_2 < \ldots < \alpha J_{-1}$. The same probability equations can be written for ordered logit models (ordered logit models were also estimated and produced very comparable results). The maximum likelihood function and its derivatives can then be obtained and optimization can be done by the usual means.

3. Roadway sections

The 1996 and 1997 crash data for the Central Florida area were used in this part of the study. The Central Florida area consists of three counties: Orange, Osceola, and Seminole. The data were obtained from the Florida traffic crash database. In both years, a total of 17,647 drivers were involved in 7,891 reported traffic crashes. The majority of the crashes are two-vehicle crashes (70.3%). The driver injury distribution for both years is: property damage only (no injury; 58.8%); possible injuries (20.7%); evident injuries (9.0%); and severe/fatal injuries (4.8%). Property damage only crashes are usually a common concern in any crash data because of the problem of under reporting. It should not be of concern in achieving the objectives of this study, since comparing the factors that affect injury severity across locations would not be affected because the source of data is the same for all models.

Variables related to the driver, vehicle, roadway, and environmental conditions were examined in the model. Drivers' variables include age, gender, alcohol involvement, and use of seat belt. Vehicle-related factors include type (regular passenger car, van, and pickup/light truck), point of impact, and speed ratio. The speed ratio variable is defined as the ratio of the estimated running speed at the time of a crash to the posted speed limit at the location of the crash, representing a measure of speeding (Abdel-Aty, Chen, Radwan, & Brady, 1999; Abdel-Aty, Chen, & Schott, 1998). Roadway and environment variables include area type (urban vs. rural), lighting condition, peak indicator (peak traffic or not), weather condition, and traffic way character (curve or straight section). Several categories of driver injury severity levels were attempted, the best fitting model had four levels: no injury, possible injury, evident injury, and severe/fatal.

The final ordered probit model is presented in Table 1. The peak period and weather variables were not significant. Driving under the influence was not significant, but the interaction between it and the seat belt factor was found to be significant. The results indicated that female drivers have a higher probability of increased severity. Older drivers have a higher probability of more severe injuries. Abdel-Aty et al. (1998) found that the risk of injuries is high for drivers over 65 years, and specifically high for drivers above 80 years old. The odds multipliers for fatalities calculated based on the results of a log-linear model was 1.43 and 2.91 for drivers between the age of 65 to 79 and above 80 years old, respectively. Speed ratio, a measure of speeding, increases the probability of severe injuries. Drivers in passenger cars

Table 1
Ordered probit model of roadway sections

Variable	Coef.	t-stat.
Constant	− 0.730	− 9.96
Driver age	0.003	4.25
Driver gender (1 if female, 0 if male)	0.405	15.42
Using seat belt at the time of crash (1 if not in use, 0 if in use)	0.553	12.55
Vehicle type (1 if passenger car)	0.266	9.08
Point of impact (1 if driver side)	0.193	4.74
Speed ratio (running speed/post speed)	0.405	9.76
Traffic way character (1 if curve)	0.186	3.43
Lighting condition (1 if daylight)	− 0.0887	− 2.13
Area type (1 if rural, 0 if urban)	0.190	7.47
Alcohol-Seat belt interaction (1 if drunk driver and not using seat belt)	0.177	2.20
Thresholds		
$\alpha 1$	0.650	48.78
$\alpha 2$	1.554	63.77
Likelihood ratio index (ρ^2)	0.093	

and drivers struck at their side are more likely to experience higher injury severity level than those of passenger vans or pickup trucks. Not wearing the seat belt increased the probability of severe injury. Crashes at curves and those in rural areas are more likely to produce injuries. Crashes in daylight were less injurious. There was an interaction effect of alcohol and seat belt use, with an increase in the probability of an injury if the driver was under the influence of alcohol and not wearing a seat belt.

4. Signalized intersections

This part of the analysis focuses on two-vehicle crashes that occurred at signalized intersections in the Central Florida area during 1996 and 1997. A total of 2,336 drivers were involved in 1,168 traffic crashes reported during these years, with 1,088 (46.6%) of those involvements resulting in no injury, 1,108 (47.4%) were possible/evident injuries, and 140 (6.0%) were severe/fatal injuries. The same variables that were explained above were tried in the ordered probit

Table 2
Ordered probit model of drivers' injury severity at signalized intersections

Variable	Coef.	t-stat.
Constant	0.156	3.02
Driver age	0.003	1.98
Driver gender (1 if female, 0 if male)	0.490	8.67
Driver fault (1 driver at fault, 0 driver not at fault)	− 0.220	− 4.17
Seat belt (1 not in use, 0 in use)	0.648	7.78
Vehicle type (1 if passenger car, 0 otherwise)	0.300	5.28
Point of impact (1 if driver side, 0 otherwise)	0.114	1.98
Speed ratio (running speed/post speed)	0.223	2.77
Area type (1 if rural, 0 if urban)	0.202	3.86
Light-weather interaction (1 if bad weather and street is dark)	0.067	2.01
Threshold α_1	0.653	23.71
Likelihood ratio index (ρ^2)	0.15	

Table 3
Ordered probit model of driver injury severity at toll plazas

Variable	Coef.	t-stat.
Constant	− 0.620	− 5.081
Driver age (1 if the driver older than 65 years)	0.661	2.643
Driver gender (1 if male, 0 if female)	− 0.359	− 3.593
E-Pass usage (1 if vehicle is equipped with E-Pass transponder, 0 otherwise)	0.593	5.092
Using seat belt at the time of crash (1 if seat belt is not in use, 0 otherwise)	1.506	7.731
Vehicle type (1 if truck, 0 otherwise)	− 0.384	− 2.479
Speed ratio indicator (1 if speed ratio is greater than 1, 0 otherwise)	0.514	2.131
Point of impact (1 if point of impact is driver side)	0.936	7.717
Weather condition (1 if weather condition is clear)	− 0.285	− 2.853
Number of impacts (1 is more than one impact, 0 otherwise)	1.427	7.658
Stopped in E-Pass lane (1 if driver stopped in E-Pass lane, 0 otherwise)	0.813	5.006
Alcohol E-Pass interaction (1 if drunk driver and E-Pass user, 0 otherwise)	1.404	4.975
E-Pass and number of impacts interaction (1 if E-Pass user and number of impacts is more than one, 0 otherwise)	1.328	4.580
Alcohol seat-belt interaction (1 if drunk driver and not wearing seat belt, 0 otherwise)	1.877	7.975
Passenger car speed ratio interaction (1 if vehicle is passenger car and speed ratio is greater than 1, 0 otherwise)	1.009	3.584
Thresholds		
α_1	0.859	13.856
α_2	2.223	16.625
Likelihood ratio index (ρ^2)	0.20	

Table 4
Simple multinomial logit model for driver's injury severity

Variable	Estimated coeff.	t-stat.
No-injury specific constant	2.304	5.92
Evident injury specific constant	1.366	4.28
Driver age, specific to no injury	− 0.016	− 2.20
Driver gender (1 if driver is male, 0 if female), specific to no injury	0.411	2.21
Alcohol-impaired driving indicator1 (1 if driver had been drinking), specific to no injury	− 0.770	− 2.31
E-Pass usage indicator1 (1 if vehicle is equipped with E-Pass transponder), specific to no injury	− 0.524	− 2.86
Passenger car indicator (1 if vehicle type is passenger car), specific to no injury	− 0.484	− 2.51
Using seat belt at the time of crash (1 if seat belt was not in use, 0 if seat belt was in use), specific to evident injury	− 1.934	− 5.93
Using seat belt at the time of crash (1 if seat belt was not in use, 0 if seat belt was in use), specific to severe/fatal injuries	− 3.261	− 6.39
Stopped in E-Pass lane (1 if driver stopped in E-Pass lane, 0 otherwise), specific to no injury	− 0.887	− 2.89
Number of impacts (1 if more than one impact, 0 otherwise), specific to possible injury	1.151	4.35
Point of impact (1 if driver side, 0 otherwise), specific to evident injury	0.744	2.65
ρ^2	0.105	

model of injury severity at signalized intersections. After attempting four categories as with the case of the previous model, injury severity was represented by three categories because it produced the best fit for the model.

Table 2 summarizes the calibration results of the ordered probit model. As with the previous model, the significant variables include: (a) driver age and gender, (b) vehicle type, (c) not wearing a seat belt, (d) point of impact, (e) speed ratio, and (f) area type. In addition, an interaction term between bad weather and dark-street lighting conditions was also significant. A surprising result, which likely needs more research, was the significant negative effect of drivers at fault. This indicates that drivers who were at fault at the time of the crash experience less severe injuries. However, a possible interpretation is that perhaps a driver at fault is typically the driver of the striking vehicle. It is more likely particularly in angle and turning crashes, which are common at intersections, that the driver of the struck vehicle experiences higher level of injuries.

5. Toll plazas

The Central Florida expressway system encompasses three state roads: SR 408, SR 417, and SR 528 totaling 127.1 km (79 miles) in length. The network consists of 10 mainline toll plazas and 42 on/off ramp toll plazas. Users pay tolls at the 10 mainline toll plazas as well as some of the on/off ramps. The total weekday Annual Average Daily Traffic (AADT) that passes through the 10 mainline toll plazas is approximately 420,000 vehicles (OOCEA, 1999). In 1994, the Central Florida expressway system authority started installing an electronic toll collection system (known as E-Pass) on the mainline toll plazas and the tolled ramps. By the end of October 1995, the initial installation was completed at the majority of the mainline toll plazas and the tolled ramps on the system. As of May 1998, dedicated E-Pass (E-Pass only) lanes have been opened at all the mainline toll plazas.

All available police reports for crashes that occurred in the vicinity of toll plazas were obtained for the Central Florida expressway system. Only the 1999 and 2000 police reports were available. These police crash reports were used to construct the database that was used in this study. The database was constructed to include all available variables that are related to crash, driver, vehicle, plaza, and road/environment. Crash-related factors include crash location with respect to the plaza structure, crash type, and number of vehicles involved in the crash. Driver factors include age, gender, driver license type, alcohol involvement, driver violation, stopped in E-Pass lane or not, and whether the driver is an E-Pass user or not. Vehicle characteristics

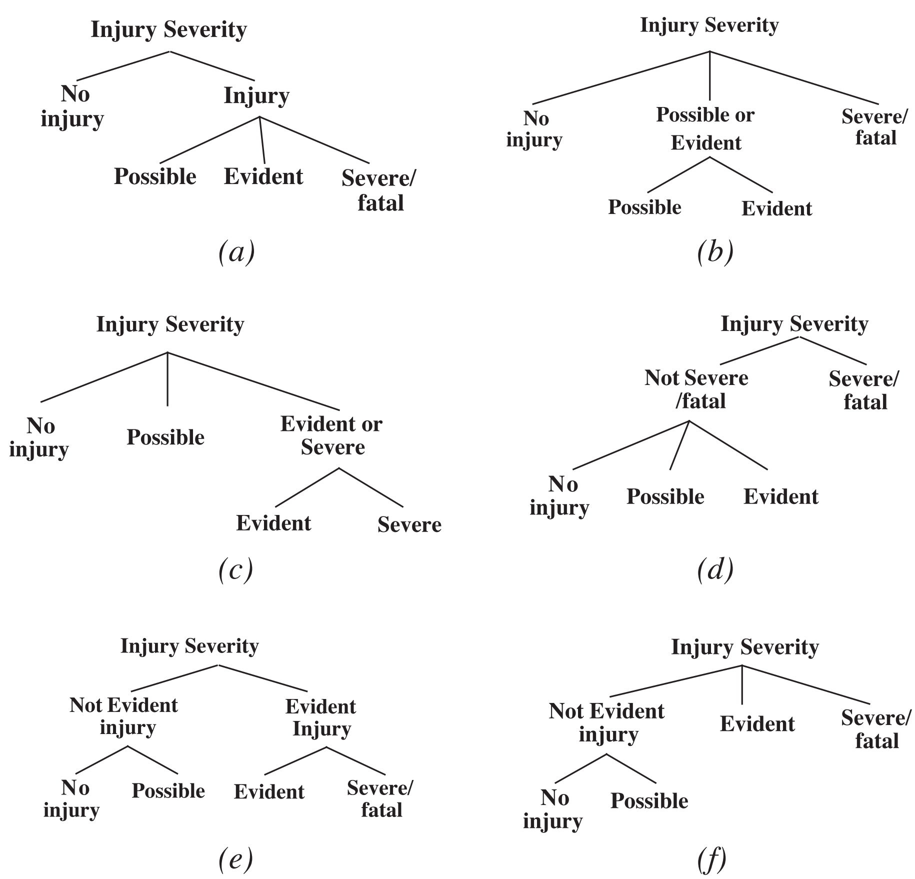

Fig. 1. Possible two-level nesting structures for drivers' injury severity.

include vehicle type, point of impact, number of impacts, and speed ratio. The speed ratio variable is defined as the ratio of the estimated running speed at the time of a crash to the posted speed limit at the location of the crash. Plaza factors include the type of toll plaza (mainline versus ramp). The road/environmental factors include weather condition, lighting condition, and time and day of the crash.

The total reported number of crashes that occurred on the expressway system was 936 and 996 for years 1999 and 2000, respectively. In these 1,932 crashes, 447 (23.1%) crashes occurred in the vicinity of toll plazas, with a total of 803 involved vehicles (drivers). The crash distribution by type of collision is rear end (40.1%), sideswipe (26.5%), hit a fixed object (21.3%), backed-into (6.4%), and other types (5.7%). Out of the 803 involved drivers, information was missing for 78 because of hit-and-run driver's action.

A unique set of variables was extracted from the description of the crash scene (which is attached to the crash report) such as crash location with respect to plaza, plaza type, whether the driver is an E-Pass user or not, and/or whether the driver stopped in the E-Pass lane or not. After screening out the cases with incomplete information, a database of 725 vehicles (drivers) was used in this analysis. Of the 725 drivers, 316 (43.6%) were involved in a crash while approaching a toll plaza (before toll plaza), 317 (43.7%) were involved in a crash at a toll plaza, and 92 (12.7%) were involved in a crash while leaving the toll plaza after paying tolls. The injury severity distribution was 61.0%, 21.0%, 15.3%, and 2.8% for no injury, possible injury, evident injury, and severe/fatal injury, respectively.

Table 3 presents the estimation results of the model. As with the previous two models, drivers' age, gender, seat belt use, speed ratio, point of impact, and vehicle type were significant in the model. Other variables that are specific to toll roads were found significant. This includes whether the vehicle is equipped with an electronic toll collection system (E-Pass), and whether the driver stopped in an E-Pass lane. The probability of higher injury levels increase if the vehicle is equipped with E-Pass. Drivers stopping in an E-Pass lane also are more likely to have severe injuries. E-Pass also entered in an interaction term with driving under the influence of alcohol, indicating that drivers under the influence of alcohol that had E-Pass experienced higher injury severity levels. The model showed also that weather, number of impacts, and the interaction between alcohol and seat belt, passenger car and speed ratio, and E-Pass and number of impacts, affect the injury severity likelihood.

Table 5
Nested logit model (structure a) for driver's injury severity

Variable	Estimated coeff.	t-stat.
No-injury specific constant	4.020	5.71
Evident injury specific constant	1.548	1.78
Driver age, specific to no injury	− 0.018	− 2.29
Driver gender (1 if driver is male, 0 if female), specific to no injury	0.460	2.15
Alcohol-impaired driving indicator1 (1 if driver had been drinking), specific to no injury	− 0.648	− 1.96
E-Pass usage indicator1 (1 if vehicle is equipped with E-Pass transponder), specific to no injury	− 0.493	− 2.44
Passenger car indicator (1 if vehicle type is passenger car), specific to no injury	− 0.532	− 2.50
Using seat belt at the time of the crash (1 if seat belt was not in use, 0 if seat belt was in use), specific to evident injury	3.332	− 4.05
Using seat belt at the time of the crash (1 if seat belt was not in use, 0 if seat belt was in use), specific to severe/fatal injuries	− 12.331	− 3.82
Stopped in E-Pass lane (1 if driver stopped in E-Pass lane, 0 otherwise), specific to no injury	− 0.946	− 2.75
Number of impacts (1 if more than one impact, 0 otherwise), specific to possible injury	2.427	5.82
Point of impact (1 if driver side, 0 otherwise), specific to evident injury	2.737	5.18
Inclusive value parameter (τ) of the injury nest	0.256*	4.88
ρ^2	0.239	

*H_o: $\tau = 1$, H_1: $\tau \neq 1$.

6. Other modeling procedures

In an attempt to test other modeling approaches, multinomial logit and nested logit models with different nesting structures were used to model injury severity. In all the applications the multinomial logit produced poor results compared to the ordered probit methodology presented earlier. Table 4 presents the multinomial logit model of crash severity levels for toll plazas.

It is clear from the model that fewer variables entered into the model and that the goodness-of-fit measure (likelihood ratio index) is lower than the ordered probit model. Another attempt was made using nested logit models. Six nesting structures were attempted as shown in Fig. 1. The nesting structure shown in Fig. 1(a) produced the best model. Table 5 depicts a nested logit model of driver injury severity at toll plazas using the nesting structure shown in Fig. 1(a). The model has a slight improvement in the likelihood ratio index, and almost no effect on the classification accuracy when compared to the ordered probit model. Also fewer variables were found significant in the nested logit model compared to the ordered probit model. Given the difficulty of estimating nested logit models because of the large number of different nesting structures that have to be attempted and based on the results of the various models estimated in this research, the ordered probit models were easy to estimate and performed very well in modeling driver injury severity.

7. Conclusions

This paper investigated the factors that affect driver injury severity at multiple locations. Ordered probit models of injury severity levels were estimated for roadway sections, signalized intersections, and toll plazas. Several factors were common across the three models such as the driver's age, gender, seat belt use, vehicle type, point of impact, and speed ratio. It is clear that wherever the crash occurs, older drivers, male drivers, and those not wearing a seat belt will have a higher probability of a severe injury. Also, drivers of passenger cars, vehicles struck at the driver's side, and those who speed, experience higher injury severity levels.

Other factors were specific to the location of the crash. Variables related to the location of the crash such as roadway curves and dark lighting conditions contribute to higher probability of injuries on roadway sections. Both signalized intersections and roadway sections models showed increased likelihood of injuries in rural areas, possibly due to higher speeds. Drivers' errors represented by whether the driver was at fault had a significant effect in the signalized intersections' model. Drivers at fault had a smaller probability of injuries, indicating a higher probability for those not at fault, which are likely the drivers of the vehicle that was struck—common in angle and turning collisions at intersections.

The model of injury severity levels at toll plazas illustrated the significance of different variables, particularly those specific to toll roads. If the vehicle is equipped with an electronic toll collection device (E-Pass), then there is a larger probability that the drivers will have an injury. This might be related to higher speeds at the toll plazas, also related is the case when drivers stop in the E-Pass lane, which is very common when a driver of a vehicle that has no E-Pass enters an E-Pass lane by mistake and stops in an attempt to pay the toll or change the lane. The effect of the interaction of E-Pass and alcohol involvement is also shown in the model.

This analysis points to different issues that can be dealt with to reduce injury severity in general. This could include safety awareness campaigns that encourage wearing the seat belt and not speeding, and discourage driving under the influence of alcohol. It also points to specific problems at certain locations that have to be improved. For example, on toll roads, better signage that warn drivers of non E-Pass equipped vehicles of not stopping in E-Pass lanes, and direct them to lanes where they can pay their tolls in other methods, are needed. Toll plazas that have no plaza structure, particularly for vehicles equipped with E-Pass, could reduce injury severity levels by reducing collisions with fixed objects.

Comparing different modeling techniques showed that the ordered probit approach is simple and produces better results than the multinomial logit approach. It also produced similar results to the nested logit method, but given the complexity in identifying the nesting structure, the ordered probit approach is recommended to model driver injury severity.

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