

ALTERNATIVE ORDERED RESPONSE FRAMEWORKS FOR EXAMINING PEDESTRIAN INJURY SEVERITY IN NEW YORK CITY

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ABSTRACT

This paper focuses on identifying the appropriate ordered response structure for modeling pedestrian injury severity. The alternative ordered response approaches considered for the empirical analysis include: ordered logit model (OL), generalized ordered logit model (GOL) and latent segmentation based ordered logit model (LSOL). The GOL and LSOL models enhance the traditional OL model in different ways. The GOL model relaxes the restrictive thresholds in the OL model by allowing for individual level exogenous variable impacts on the threshold parameters. On the other hand, the LSOL model allows for differential impact on the alternatives by segmenting the pedestrian crash population into various segments with segment specific OL parameters. In our study, we focus on examining the performance of these two model structures relative to the traditional OL model in the context of pedestrian injury severity. The performance of the formulated injury severity models are tested based on the “New York City (NYC) Pedestrian Research Data Base” for the years 2002 through 2006. To our knowledge, the study provides a first of its kind comparison exercise among OL, GOL and LSOL models for examining pedestrian injury severity. The model estimation results clearly highlight the presence of segmentation based on the crash location attributes of pedestrian accidents. The crash location attributes that affect the allocation of pedestrians into these segments include: regional county, functional classification of roadway, pedestrian location on roadway, number of travel lanes and number of parking lanes in the roadway system. The key factors influencing pedestrian injury severity are weather condition, lighting condition, vehicle types, pedestrian age and season. Overall, the results of the empirical analysis provide credence to the hypothesis that LSOL model is a promising ordered framework to accommodate population heterogeneity in the context of pedestrian injury severity.

Keywords: Pedestrian safety, Comparison of ordered response models, Generalized ordered logit model, Latent segmentation based ordered logit model, Validation

INTRODUCTION

Pedestrian safety is a global-health concern and the United States of America is no exception. Earlier research reveals that the risk of being injured while walking could be about four times higher than driving an auto (Elvik, 2009). In 2008, about 4,378 pedestrian fatalities and 69,000 other pedestrian injuries from road traffic crashes were recorded in the United States (NHTSA, 2009). More alarmingly, about 72 percent of these fatalities occurred in urban areas underscoring the need for examining urban pedestrian safety. To study pedestrian safety issues in urban regions, we focus on pedestrian crash injury severity data from the largest and most populous urbanized area of US, New York City (NYC). In NYC, approximately 10% of the journey-to-work trips are conducted on foot (Ukkusuri et al., 2012), while the national average for journey-to-work trips is approximately 6% (Loukaitou-Sideris et al., 2007). However, the city has a poor pedestrian safety record compared to rest of the nation. The pedestrian fatality rate is almost five folds higher in NYC compared to the whole nation (pedestrian fatality rate is 11% in US and 52% in NYC) (NHTSA, 2009; NYCDOT, 2010). On the NYC street, pedestrians are 10 times more likely to die than a motor vehicle occupant and the annual cost of these pedestrian crashes is as high as \$1.38 billion (NYCDOT, 2010) - approximately 32% of total traffic crash costs of the city. These statistics clearly indicate that pedestrian safety is of great concern for NYC region. Any effort to reduce the social burden of these crashes and enhance pedestrian safety would necessitate the examination of factors that contribute significantly to crash likelihood and/or pedestrian injury severity in the event of a crash. This study endeavours to identify the various factors that affect pedestrian crash severity in a pedestrian-motor vehicle crash in NYC by developing econometric models that quantify the impact of these factors on injury severity.

A critical component in the process of identifying the contributing factors is the application of appropriate econometric model. Pedestrian injury severity is often reported as an ordered variable resulting in the application of ordered response models for analyzing risk factors. The most commonly employed approach to pedestrian injury severity is the ordered logit/probit (OL/OP) models. These models recognize the inherent ordering in the severity variable while apportioning the probability of injury severity to various alternatives based on population specific thresholds. The traditional OL/OP model has been the workhorse for examining injury severity in safety literature. However, the traditional ordered response model imposes strong restrictions on the structure of threshold parameters. Specifically, the traditional OL/OP model assumes the thresholds to remain fixed across crashes (Eluru et al., 2008). However, it is possible that depending on the individual and crash attributes the thresholds could vary across crashes.

In recent years, two enhanced econometric frameworks have been proposed and implemented in transportation safety literature allowing us to tackle the restriction on the threshold parameters in the traditional OL model. These advanced frameworks include: 1) Generalized Ordered Logit (GOL) (Eluru et al., 2008) and 2) Latent segmentation based Ordered Logit (LSOL) model (Eluru et al., 2012). The GOL model relaxes the restrictive assumption by allowing the threshold in the traditional OL model to vary based on individual and crash attributes. On the other hand, the LSOL model relaxes the assumption of the traditional OL model by categorizing pedestrian crashes into different segments based on crash location attributes while estimating segment specific OL parameters. The pedestrians involved in crashes are assigned to the various segments probabilistically as a function of individual level exogenous variables. The two approaches represent crash injury severity more realistically compared to the

traditional OL model and improve the accuracy in quantifying the impact of exogenous variables on pedestrian injury severity (Eluru et al., 2008; Eluru et al., 2012). However, there has been no research conducted on examining which of these two approaches offers a better framework for injury severity analysis. In our study, we undertake a comparison exercise to identify the preferred ordered model for examining pedestrian injury severity. The comparison exercise is conducted based on the performance of the various ordered response frameworks in model estimation as well as in model validation (using a hold-out sample).

The rest of the paper is organized as follows. Section 2 provides a discussion of earlier research on pedestrian injury severity modeling while positioning the current study. Section 3 provides details of the various econometric model frameworks used in the analyses. In Section 4, the data source and sample formation procedures are described. The model estimation results, elasticity effects and validation measures are presented in Section 5. Section 6 concludes the paper and presents directions for future research along with the recommendations.

EARLIER RESEARCH

A number of research efforts have examined pedestrian crashes to gain a comprehensive understanding of the factors that affect crash frequency and severity. A category of these studies has focused on pedestrian crash frequencies (Gårder, 2004), or on the exposure measure of pedestrian crash risk (Keall, 1995) while another category of studies has examined the determinants of injury severity in the event of a pedestrian crash. The review in our study is restricted to the latter category. A summary of earlier research on pedestrian injury severity analysis is provided in Table 1. The table provides information on the analysis framework employed, pedestrian injury severity representation, and characteristics/factors considered in the analysis (including crash characteristics, vehicular characteristics, roadway design and land use attributes, environmental factors, pedestrian characteristics and driver characteristics).

The following observations may be made from the review presented in Table 1. *First*, the dependent variable examined in most of the earlier studies is pedestrian injury severity ranging from two (killed/severe injury to slight injury/PDO) to five (fatality, disabling injury, not disabling injury, probable injury to no injury) severity levels. *Second*, the most prevalent mechanism to study pedestrian injury severity is logistic regression and OL/OP models (fourteen out of nineteen). *Third*, only two earlier research efforts (Eluru et al., 2008; Kim et al., 2008a) have considered variables from all factor categories. *Fourth*, the unordered response structure predominantly considered is the multinomial logit model (or its mixed version). *Fifth*, only two of the studies (Eluru et al., 2008; Clifton et al., 2009) considered the generalized version of ordered response model and notably none of the earlier studies have considered latent segmentation based models for examining pedestrian injury severity. *Finally*, two studies (Eluru et al., 2008; Rifaat et al., 2011) examined both the pedestrian and bicyclist crash severities together in their empirical analysis.

The overall findings from earlier research efforts are usually consistent. The most common factors that increase pedestrian crash severities include: older pedestrians, male pedestrians, intoxicated pedestrians and/or drivers, occurrence of crash in darkness (with or without lighting), vehicle speeding, crash location is in a commercial area or on highways, and crash with bus or truck. On the other hand, exogenous factors that reduce the pedestrian crash severities include: older drivers, presence of traffic signal control, snowy weather and crash occurrence during the day.

This Study in Context

As is evident from the review presented in preceding section, many studies in earlier literature have employed traditional ordered and unordered outcome models. The traditional ordered response model imposes a restrictive assumption on the impact of exogenous variables by constraining their impact to be the same for all alternatives. Towards addressing this limitation, researchers have employed the unordered response models that allow the impact of exogenous variables to vary across the injury severity levels. A sample of recent research efforts used both the ordered and unordered response models for pedestrian crash severity analysis and find that the implications obtained from the two model systems differ for some variables (Abay, 2013; Kwizile et al., 2011). In both studies, the unordered systems fit the data better than the ordered systems indicating that the additional flexibility of estimating alternative specific parameters is resulting in an improved fit. However, the increased flexibility from the unordered models is obtained at a cost. The unordered response models neglect the inherent ordering of crash severity outcome.

Ideally, it would be beneficial to incorporate the influence of alternative specific effects of exogenous variable in the ordered response framework. The generalized ordered response model (or proportional odds logit) (Eluru et al., 2008; Clifton et al., 2009; Castro et al., 2013; Quddus et al., 2010; Eluru 2013; Yasmin and Eluru, 2013; Yasmin et al., 2012, Mooradian et al., 2013; Wang and Abdel-Aty, 2008) relaxes the restrictive assumption of the traditional ordered response model by allowing for differential impact of exogenous variables on injury severity levels. Recent evidence on the comparison of the unordered models and generalized ordered response systems in the context of injury severity highlight how the generalized ordered response model offers the same flexibility (if not better) as that of the unordered systems (Yasmin and Eluru, 2013 and Eluru, 2013). Hence it is important that pedestrian injury severity models consider the generalized ordered response framework.

In recent years, there has also been a revival of latent segmentation models in safety and transportation. The traditional discrete outcome models restrict the impact of exogenous variables to be same across all crash locations – homogeneity assumption. But, the impact of control variables on pedestrian crash severity might vary across individuals based on crash location attributes. To illustrate this, let us consider the pedestrian crash severity outcomes at two different crash locations (L1 and L2). For the ease of comparison, let us also assume that all crash attributes are identical with the only difference between the two scenarios being the location; suppose L1 is an intersection and L2 is a mid-block location. Now let us consider the influence of “dark road - lighted” variable in these crash locations. In the first crash at L1, the driver might be travelling at a lower speed while approaching an intersection thus requiring a smaller reaction time to reduce the impact of crash with a pedestrian at this location. In this case, the illumination of road light might help both the drivers and pedestrians to be more heedful in their movements and thus result in a less severe injury for pedestrians. On the other hand, at location L2, the driver would not have stopped and possibly would be travelling at a higher speed as he/she would not expect any pedestrian at mid-block location. In this event, the advantages of having illumination at the dark period would be reduced and the higher impact force would increase the pedestrian crash severity at L2. This is an example of how pedestrian location at the time of crash moderates the influence of one variable (dark road – lighted) in determining pedestrian crash severity outcomes. However, it is possible that crash locations might serve as a moderating influence on multiple control variables in the context of pedestrian

injury severity. Ignoring such heterogeneous impact of variable might result in incorrect coefficient estimates.

A common approach employed to accommodate heterogeneity, in discrete outcome models, is the estimation of mixed/random coefficients version of the discrete outcome models (for example Eluru and Bhat, 2007; Paleti et al., 2010; Srinivasan, 2002; Morgan and Mannering, 2011; Kim et al., 2013; Xiong and Mannering, 2013)¹. However, in this approach the focus is on incorporating unobserved heterogeneity through the error term while also necessitating extensive amount of simulation for model estimation. In an attempt to accommodate for systematic heterogeneity researchers have considered segmenting the population based on exogenous variables (such as gender, age, location) and estimate separate models for each segment (see Aziz et al., 2013 for segmentation based on location). These approaches divide the population into groups and are meaningful only for 1 or 2 exogenous variables. When segmentation by many variables is considered simultaneously it results in a large number of data samples necessitating a huge number of model estimations and also might lead to very few records in the various samples. To address this limitation, more advanced approaches such as clustering techniques that allow us to segment based on a multivariate set of factors have been suggested. The approach has been successfully employed (Mohamed et al., 2013) in examining the pedestrian crash severity. However, the approach still requires allocating data records exclusively to a particular segment. So it is possible that some clusters end up with very little records (as was the case for one or two clusters in Mohamed et al., 2013).

An alternative approach to accommodate for population heterogeneity is to undertake an endogenous segmentation approach. In this approach crash records are allocated probabilistically to different segments and a segment specific model is estimated for each segment. The approach does not allocate data records exclusively and hence allows the segment specific models to be estimated on the entire population (as opposed to data records allocated to the segment in clustering or simple segmentation approaches). Also, unlike the mixed models, it does not require any specific distributional assumption for the parameters (Greene and Hensher, 2003). The probabilistic allocation improves model estimation efficiency and is appropriate irrespective of the sample size of the dataset *i.e.* it works efficiently for large and small datasets. On the other hand, the clustering approach is suitable only when we have a large dataset. The endogenous segmentation approach, also referred to as the latent segmentation approach, has been employed in safety literature recently (Eluru et al., 2012; Xie et al., 2012).

The current research draws on these advances to contribute to pedestrian injury severity modeling along two directions. *First*, the study contributes to econometric modeling by identifying the appropriate framework for examining pedestrian injury severity through an exhaustive comparison exercise across three ordered response models (OL, GOL and LSOL models). The models estimated are rigorously compared employing various comparison metrics for estimation and validation. *Second*, the study contributes substantively by identifying the various determinants of pedestrian injury severity in NYC allowing us to suggest remedial measures to improve pedestrian safety. The ordered response models are estimated using an exhaustive set of exogenous variables (crash characteristics, environmental factors, vehicle characteristics, roadway design and operational attributes, land use characteristics and pedestrian characteristics).

¹ The readers are encouraged to review Yasmin and Eluru, 2013 for an extensive review of discrete outcome modeling approaches employed in transportation safety literature (not just pedestrian literature).

ECONOMETRIC FRAMEWORK

In this section, we provide the brief discussion of the methodology of all the models considered for examining pedestrian injury severity in our research.

Standard Ordered Logit Model

In the traditional ordered response model, the discrete injury severity levels (y_i) are assumed to be associated with an underlying continuous latent variable (y_i^*). This latent variable is typically specified as the following linear function:

$$y_i^* = \mathbf{X}_i\boldsymbol{\beta} + \varepsilon_i, \text{ for } i = 1, 2, \dots, N \quad (1)$$

where,

i ($i = 1, 2, \dots, N$) represents the pedestrians

\mathbf{X}_i is a vector of exogenous variables (excluding a constant)

$\boldsymbol{\beta}$ is a vector of unknown parameters to be estimated

ε is the random disturbance term assumed to be standard logistic

Let j ($j = 1, 2, \dots, J$) denotes the injury severity levels and τ_j represents the thresholds associated with these severity levels. These unknown τ_j s are assumed to partition the propensity into $J - 1$ intervals. The unobservable latent variable y_i^* is related to the observable ordinal variable y_i by the τ_j with a response mechanism of the following form:

$$y_i = j, \text{ if } \tau_{j-1} < y_i^* < \tau_j, \text{ for } j = 1, 2, \dots, J \quad (2)$$

In order to ensure the well-defined intervals and natural ordering of observed severity, the thresholds are assumed to be ascending in order, such that $\tau_0 < \tau_1 < \dots < \tau_J$ where $\tau_0 = -\infty$ and $\tau_J = +\infty$. Given these relationships across the different parameters, the resulting probability expressions for individual i and alternative j for the OL model take the following form:

$$\pi_{ij} = Pr(y_i = j | X_i) = \Lambda(\tau_j - \mathbf{X}_i\boldsymbol{\beta}) - \Lambda(\tau_{j-1} - \mathbf{X}_i\boldsymbol{\beta}) \quad (3)$$

where $\Lambda(\cdot)$ represents the standard logistic cumulative distribution function.

Generalized Ordered Logit Model

The GOL model relaxes the constant threshold across population restriction to provide a flexible form of the traditional OL model. The basic idea of the GOL is to represent the threshold parameters as a linear function of exogenous variables (Maddala, 1983; Terza, 1985; Srinivasan, 2002; Eluru et al., 2008). Thus the thresholds are expressed as:

$$\tau_j = fn(Z_{ij}) \quad (4)$$

where, Z_{ij} is a set of exogenous variable (including a constant) associated with j th threshold. Further, to ensure the accepted ordering of observed discrete severity ($-\infty < \tau_1 < \tau_2 < \dots < \tau_{j-1} < +\infty$), we employ the following parametric form as employed by Eluru et al., (2008):

$$\tau_j = \tau_{j-1} + \exp(\delta_j \mathbf{Z}_{ij}) \quad (5)$$

where, δ_j is a vector of parameters to be estimated. The remaining structure and probability expressions are similar to the OL model. For identification reasons, we need to restrict one of the δ_j vectors to zero.

Latent Segmentation Based Ordered Logit Model

Standard ordered response model restricts the impact of crash related explanatory variables to be identical for all individuals (Eluru et al., 2008). The latent segmentation model relaxes this homogeneity assumption of the standard ordered response model by classifying the crashes based on crash location attributes and subsequently model the effect of crash attributes within each segment separately (Eluru et al., 2012). Let us consider S homogenous segments of crash locations. The multinomial logit structure is used to assign the pedestrians to these segments based on the attributes of crash locations. The utility for assigning a pedestrian i 's crash location to segment s is defined as:

$$U_{is}^* = \alpha'_s \mathbf{Z}_i + \xi_{is} \quad (6)$$

where

α'_s is a vector of coefficients

\mathbf{Z}_i is a vector of attributes that influences the propensity of belonging to segment s

ξ_{is} is an idiosyncratic random error term assumed to be identically and independently

Type 1 Extreme Value distributed across individual i and segment s .

Then the probability that pedestrian i 's crash location belongs to segment s is given as:

$$P_{is} = \frac{\exp[\alpha'_s \mathbf{Z}_i]}{\sum_s \exp[\alpha'_s \mathbf{Z}_i]} \quad (7)$$

Within the latent segmentation approach, the unconditional probability of individual sustaining injury severity level j is given as:

$$P_i(j) = \sum_{s=1}^S (P_i(j)|s)(P_{is}) \quad (8)$$

where, $P_i(j)|S$ represents the probability of pedestrian i sustaining injury severity level j within the segment s . Now, if we consider the injury severity sustain by pedestrian i to be ordered and if the accident belongs to segment s , we can represent the latent propensity function as follows as in standard OL model:

$$y_{is}^* = \mathbf{X}_i \boldsymbol{\beta}'_s + \varepsilon_{is}, \text{ for } i = 1, 2, \dots, N \quad (9)$$

Thus, the probability expressions take the form:

$$P_i(j)|s = \Lambda(\tau_{sj} - \mathbf{X}_i \boldsymbol{\beta}'_s) - \Lambda(\tau_{s,j-1} - \mathbf{X}_i \boldsymbol{\beta}'_s) \quad (10)$$

where $\Lambda(\cdot)$ represents the standard logistic cumulative distribution function.

DATA

Data Source

The pedestrian crash data for NYC used in the research effort is extracted from “NYC Pedestrian Research Data Base” for the year of 2002 through 2006. The coded information of this database is compiled from three different data sources: 1) New York State Department of Transportation-Safety Management System (NYSDOT SMS) data, 2) New York City Department of Transportation (NYCDOT) data and 3) US Census data. The NYC pedestrian research database consists of a total of 7,354 crashes involving at least one pedestrian during this five-year period. These crashes involve about 7,647 pedestrians and 7,712 motor vehicles resulting in 739 fatalities and 6,710 serious injuries to the pedestrians. A number of crash-related factors are extracted from these databases to explore the effect of various exogenous variables on pedestrian injury severity.

Sample Formation and Description

In an effort to clearly examine the influence of exogenous variables on pedestrian injury severity, we limit our attention to crashes involving one pedestrian and one vehicle. Further, records with missing information for essential attributes were also removed. The final compiled dataset consisted of 4,701 records. In this final sample of accidents, the proportions of injury severity for the reported categories were as follows: a) property damage only (PDO) – 0.4%, b) minor injury – 1.0%, c) serious injury – 89.0%, and d) fatal injury – 9.7%. To obtain a reasonable sample share for all alternatives the PDO and minor injury categories were merged for our analysis. From the final dataset, 4,258 records are sampled out for the purpose of model estimation and the remaining 443 records are set aside for validation. Table 2 offers a summary of the sample characteristics of the dataset. From the descriptive analysis, we observe that a large portion of crashes occur at an intersection (72.3%), in clear weather (71.9%), in the presence of daylight (56.3%) and on urban streets (96.9%). The majority of pedestrians are adult (59.2%) and mostly struck by a passenger vehicle (74.1%).

EMPIRICAL ANALYSIS

Variables Considered

For our analysis, we selected variables from six broad categories: crash characteristics (crash location), environmental factors (weather condition, season and lighting condition) vehicle characteristics (type of vehicle), roadway design and operational attributes (roadway class², travel lane and parking lane), land use characteristics (boroughs) and pedestrian characteristics (pedestrian age). The impact of several variables such as presence of shoulder, shoulder width, vehicle weight, point of impact, pedestrian condition, driver condition, at fault-status and time of day could not be explored, because the information for these variables was either entirely unavailable or there was a large fraction of missing data for these attributes in the dataset. To be sure, we employed lighting condition and vehicle type to act as surrogates for time of day and vehicle weight, respectively. In the final specification of model, statistically insignificant variables were removed through a systematic process based on statistical significance (90% significance) from the universal variable set. The insignificant variables from our analysis

² Roadway class served as a surrogate for speed limit.

include day-of-week and trajectory of vehicle's motion. Further, in cases where the variable effects were not significantly different across different variable levels the coefficients were restricted to be the same.

Overall Measures of Fit

We estimated four models: 1) OL, 2) GOL, 3) LSOL with two segments (LSOL II) and 4) LSOL with three segments (LSOL III). After extensively testing for three segments in latent segmentation approach we found that the model collapses to the two segment model. Hence, from here on, the entire comparison exercise is focussed on three models: OL, GOL and LSOL II. Prior to discussing the estimation results, we compare the performance of these models. The GOL is a generalized version of OL. Thus, we can compare these two models by using likelihood ratio test for selecting the preferred model. However, the comparison with the LSOL II model using the likelihood ratio is not possible because these structures are not nested within one another. Hence, we employ different measures that are routinely applied in comparing econometric models including: 1) Bayesian Information Criterion (BIC), 2) Akaike Information Criterion corrected (AICc)³ and 3) Ben-Akiva and Lerman's adjusted likelihood ratio (BL) test. These estimates are presented in Table 3.

The BIC for a given empirical model is equal to $-2\ln(L) + K \ln(Q)$ and the AICc for an empirical model is given by $AIC + [2 K(K+1)/(Q -K-1)]$, where $\ln(L)$ is the log-likelihood value at convergence, K is the number of parameters, and Q is the number of observations. The model with the *lower* BIC and AICc values is the preferred model. The numbers in Table 3 indicate that the LSOL II model has lower values for both measures.

The BL test statistic (Ben-Akiva and Lerman, 1985) is computed as: $\lambda = \Phi \left\{ - \left[\frac{\sqrt{-2(\bar{\rho}_2^2 - \bar{\rho}_1^2)} L(C) + (M_2 - M_1)}{\bar{\rho}_1^2} \right] \right\}$, where $\bar{\rho}^2$ represents the McFadden's adjusted rho-square value for the model. It is defined as $\bar{\rho}_i^2 = 1 - \frac{L_i(\beta) - M_i}{L(C)}$, where $L_i(\beta)$ represents log-likelihood at convergence for the i^{th} model, $L(C)$ represents log-likelihood at sample shares and M_i is the number of parameters in the model (Windmeijer, 1995). The $\Phi(\cdot)$ represents the cumulative standard normal distribution function. This BL test statistic identifies if the adjusted likelihood ratio indices of the two non-nested models are significantly different. It compares two models by computing the probability (λ) that we could have obtained the higher $\bar{\rho}^2$ value for the "best" model even though this is not the case. The resulting λ values (presented in Table 3) thus clearly indicate that LSOL II offers superior fit compared to both OL and GOL models at any significance level (LSOL II has the higher $\bar{\rho}^2$ with lowest number of parameters compared to OL and GOL). The comparison exercise, therefore, highlights the superiority of the LSOL II model in terms of data fit compared to the OL and GOL models. In the following discussion, we always denote LSOL II as LSOL for simplicity.

Estimation Results

To conserve on space, the subsequent discussions of exogenous variable impacts are restricted to LSOL estimates. Table 4 presents the estimation results of the LSOL model. An intuitive

³ AICc is a more stringent version of the AIC [$AIC = 2K - 2\ln(L)$] in penalizing for additional parameters

discussion of the LSOL model is presented followed by the discussion of segmentation component parameters and severity component parameters specific to segment 1 and 2.

Intuitive Interpretation of LSOL Model

To delve into the segmentation characteristics, the model estimates are used to generate information on: 1) population share across the two segments, and 2) overall injury severity shares within each segment. These estimates are presented in Table 4. From the estimates, it is evident that the probability of pedestrians being assigned to segment 2 is substantially higher than the probability of being assigned to segment 1. Further, the likelihood of injury severity for pedestrians conditional on their belonging to a particular segment offer contrasting results indicating that two segments exhibit distinct injury severity profiles in the current research context. It is clear that pedestrians assigned to segment 1 are more likely to sustain fatalities while those assigned to segment 2 are more likely to sustain serious injury. To facilitate the discussion from here on, we label segment 1 as the “*fatality segment*” and segment 2 as the “*serious injury segment*”.

Latent Segmentation Component

The latent segmentation component determines the probability that a pedestrian is assigned to one of the two latent segments based on the crash location attributes. The latent segmentation component coefficients correspond to the likelihood of assigning pedestrians to serious injury segment. The positive sign of the constant term indicates a larger likelihood for pedestrians being assigned to serious injury segment. Crash location attributes that affect the allocation of pedestrians, into either of the segment, include: regional county, functional classification of roadway, pedestrian location on roadway, number of travel lanes and number of parking lanes in the roadway system.

NYC is composed of five boroughs: Manhattan, Bronx, Brooklyn, Queens and Staten Island. From the estimated results, we find that the likelihood of pedestrian being assigned to serious injury segment is higher for Manhattan compared to other boroughs. On the other hand, pedestrian crashes occurring in Staten Island are likely to be assigned to fatality segment. The coefficients for functional classification of roadway indicate that highways and parkways increase the likelihood of pedestrians being assigned to fatality segment. It is not surprising that these variables increase the likelihood of a pedestrian being assigned to fatality segment, because highways and parkways represent roadway facilities with the highest speeds. The result associated with the crash at mid-block location reflects an increase likelihood of pedestrian being assigned to fatality segment. Motorists may not expect pedestrians at locations not designated for them and they tend to drive at a higher speed at mid-block compared to intersection (Kim et al., 2010). Consequently, they might fail to notice the pedestrian in time leading to increased propensity of fatality. An increase in total number of travel lanes in roadway increases the likelihood of assigning the pedestrians to fatality segment. Generally, higher the number of travel lanes, higher is the width of the roadway. Wider roads imply longer exposure time for pedestrians to vehicular traffic, and higher vehicular speed, increasing the likelihood of pedestrian fatalities (Sze and Wong, 2007; Tay et al., 2011). The result associated with parking lanes indicates that an increase in number of parking lanes on roadway increase the likelihood of assigning the pedestrians to serious injury segment. The presence of on-street parking, in general,

is expected to force the drivers to be more watchful for parked cars entering the roadway or sporadic pedestrian movement as people get in and out of their vehicles (Zajac and Ivan, 2003). Overall, fatality segment is characterized by high speed facilities in the roadway system, crashes occurring at mid-block location of road, increased number of travel lanes and lower number of parking lanes in roadway system.

Injury Severity Component: Segment 1

The injury severity component within the fatality segment is discussed in this section. The interpretation of the coefficients follows the usual ordered response framework.

Weather is considered to be one of the most important environmental components that affect driving. The results presented in Table 4 indicate that snowy/foggy weather condition results in less severe pedestrian crashes compared to the clear and rainy weather. The reduced probability of severe pedestrian crashes during snowy/foggy period perhaps can be attributed to the reduced driving speed (Eluru et al., 2008; Kim et al., 2010) and more cautious pedestrian activities. The unfavourable driving conditions during adverse weather perhaps also result in increased driver attention thereby reducing the severity of pedestrian crashes.

Visibility significantly affects driver and pedestrian activity. In our study, the lighting condition has significant association with the pedestrian injury severity propensity. It is very interesting to note that crashes of fatality segment occurring in the presence of artificial illumination (street-lights) during dark periods increases the likelihood of severe pedestrian injury compared to other lighting conditions (daylight, dawn and dusk). Problems associated with darkness at night-time could be attributed to poor visual conditions, higher vehicular speed, fatigue, possible negligence, inattentiveness, driving and walking under the influence of alcohol (Sze and Wong, 2007; Lee and Abdel-Aty, 2005; Tay et al., 2011; Rifaat et al., 2011; Kim et al., 2008a; Kim et al., 2010; Montella et al., 2011). These conditions perhaps increase the reaction time and braking distance of vehicles, and lead to greater impact at the time of a crash. Further, longer response time by emergency crews at the crash location during darkness (Klop and Khattak, 1999) could also exacerbate the resulting pedestrian crash severity.

The relevance of pedestrian age has long been recognized as an important contributory factor in pedestrian crash severity studies. The model results reveal a reduction in the risk propensity for both child and teenager pedestrian groups compared to the adult group perhaps because these pedestrian groups are more physically fit (Lee and Abdel-Aty, 2005) compared to other pedestrians. Moreover, child pedestrians are less likely to be transgressors of traffic rules (Kim et al., 2008c) and thus unlikely to be involved in severe crashes. Thresholds in the ordered response model form the boundary points for different levels of injury severities. In the first segment, when the latent propensity of the individual is less than -2.87 the pedestrian sustains PDO/minor injury. The pedestrian sustains a serious injury when the propensity is between -2.87 and 0.50. The pedestrian is fatally injured when the propensity value is greater than 0.50.

Injury Severity Component: Segment 2

The OL model corresponding to serious injury segment provides variable impacts that are significantly different, in magnitude as well as in sign (for a few variables), from the impacts offered by the exogenous variables in fatality segment. Further, we also notice that the number of

variables that moderate the influence of injury severity is significantly higher for serious injury segment.

In the second segment, the results indicate that cloudy weather affects the injury sustained by a pedestrian in a crash. In particular, cloudy weather results in more severe crashes compared to the clear and rainy weather perhaps because of the reduced visibility, which presumably results in reduced perception-reaction and reduced ability to take evasive actions at the crash incident (Tay et al., 2011). Cloudy days perhaps also adversely affect human psychology. For example, Kim et al., (2008c) observed less compliance with traffic rules on behalf of both the drivers and pedestrians on a cloudy day.

The influence of lighting condition has a strikingly different influence on the pedestrians compared to the effect in fatality segment. For the dark-lighted condition, the latent propensity is found negative, which indicates a lower injury risk propensity of pedestrian in serious injury segment. This might indicate more heedful movement of pedestrians and more effective avoidance maneuver of drivers during darkness. The result also highlights how the same variable can have distinct influence on injury severity based on the segment to which the crash is allocated. The LSOL approach allows for capturing such complex interactions. With respect to vehicle type involved in a crash with pedestrian, our study results show that a pedestrian struck by a truck or a bus has a higher injury risk propensity. The reason may be attributed to the heavier vehicle mass, greater stiffness, greater momentum, large area of impact for pedestrians, higher bumper height, blunter geometry, and longer stopping distances of bus and trucks compared to other vehicles (Eluru et al., 2008; Lee and Abdel-Aty, 2005; Tay et al., 2011; Kim et al., 2008a; Montella et al., 2011). For bus, the weaving pattern of movement in traffic due to frequent on-street bus stops could also impose higher fatality risk on pedestrians.

The influence of pedestrian age on crash severity is along expected lines. It is found that the older pedestrians are associated with the higher likelihood of severe crashes compared to the adult pedestrian groups. Older pedestrians might be physically weak and they may be medically unfit with problems related to hearing, vision and contrast sensitivity (Lee and Abdel-Aty, 2005; Kim et al., 2010). Moreover, older pedestrians tend to be slow in reacting to hazardous situations, walk slower, can withstand low impact force of crash impact and may select insufficient gaps while crossing the road (Sze and Wong, 2007; Anowar et al., 2010); all of which contribute to their higher severity risk. The result associated with the season reflect that injury risk propensity of pedestrian crashes is lower in spring compared to any other season. The result is quite interesting and the reasons for the effect are not very clear. It is possibly a manifestation of some unobserved variables that are not considered in our analysis.

In the serious injury segment, when the latent propensity of the individual is less than -4.83 the pedestrian sustains PDO/minor injury. The pedestrian sustains a serious injury when the propensity is between -4.83 and 3.99. The pedestrian is fatally injured when the propensity value is greater than 3.99. This again highlights the difference between the two segments.

Elasticity Effects

The parameter effects of the exogenous variables do not provide the magnitude of the effects on injury severity. For this purpose, we compute the aggregate level “elasticity effects” for all independent variables (see Eluru and Bhat, (2007) for a discussion on the methodology for computing elasticities) and present the computed elasticities in Table 5. The effects are computed for both the GOL and LSOL models.

The following observations can be made based on the results presented in Table 5. *First*, the results from the elasticity effects indicate that there are substantial differences in the elasticity effects of these two models. For instance, the LSOL model predicts a reduction in PDO/Minor injury for pedestrians in Manhattan region while the GOL model predicts an increase in the PDO/Minor injury category. In a similar vein, differences can be observed for travel lane and dark-lighted variables. *Second*, the most significant variables in terms of fatal injury (from both models) for pedestrians are pedestrian age 65 and above, crash with a truck or bus, crash occurred on a highway or parkway. In terms of fatal injury reduction the important factors are pedestrian age between 13-18 and snowy conditions. *Finally*, the dark unlighted variable exhibits substantially different impacts in the LSOL and GOL models. The reason for the difference could be attributed to differences in the model structures of the LSOL and GOL models.

Validation Analysis

We also evaluate the performance of these models on a validation sample. We use both the aggregate and disaggregate measures of fit for the validation exercise. At the disaggregate level we calculate predictive log-likelihood (computed by calculating the log-likelihood for the predicted probabilities of the sample), probability of correct prediction (computed as the probability that the chosen alternative has the highest predicted probability), and probability of correct prediction >0.7 (computed as the probability that the chosen alternative has the highest predicted probability and it is also >0.7). At the aggregate level, root mean square error (RMSE) and mean absolute percentage error (MAPE) are computed by comparing the predicted and actual (observed) shares of injuries for each injury severity level. We compute these measures for the complete validation sample and specific sub-samples in the population - Manhattan, Cloudy weather, Dark road-lighted, Pedestrian age 12 and less and Spring. The results for computation of these measures are presented in Table 6.

At the disaggregate level the fit measures show that GOL performs marginally better than LSOL. At the aggregate level, both the RMSE and MAPE values are very close for the two model systems. It is important to note that with six fewer parameters the LSOL model performance only marginally poorly compared to the performance of the GOL model. The close performance of the two model systems is further illustrated through the computation of the validation measures for various sub-samples of the population. The results indicate that LSOL and GOL models offer very similar prediction for the various sub-samples at the aggregate and disaggregate level. The results reinforce the strengths of the LSOL model to perform very close to the GOL model.

DISCUSSION AND RECOMMENDATIONS

The results obtained in our analysis have important implications for improving the safety of pedestrians in terms of enforcement, engineering and educational strategies (3 'E' approach). With respect to enforcement and education, our results endorse a continuous education program and stricter enforcement to prevent unsafe road crossing behaviour of pedestrians. Most importantly, public education campaigns are needed to encourage the pedestrians to wear "reflectors" to increase their conspicuity in darkness (European Commission, 2007). Retroreflective materials (lamps, flashing lights or retroreflective vest) enhance the drivers'

detection of pedestrians at nighttime (Luoma et al., 1996; Kwan and Mapstone, 2009; J., Muttart, 2000; Wood, 2005) and hence in turn reduce the pedestrian crash severity.

Policies concerning the visual enhancement of pedestrians during night time; in the form of artificial illumination, increased intensity of roadway lighting, adaptive headlighting solution, illuminated crosswalk, illuminated warning sign and smart lighting; could improve pedestrian safety (Sullivan and Flannagan, 2007; Sullivan and Flannagan, 1999; Ragland et al., 2003; Polus and Katz, 1978). Enhanced visibility is identified in several previous studies to be the most cost effective measures in improving pedestrian safety and the greatest safety benefit from it is observed in reducing fatal pedestrian crashes (Ragland et al., 2003; ITE, 2002; Sullivan and Flannagan, 1999). Campaigns should also address the issue of increased fatality risk of older pedestrians and advise seniors of the potential risk and suggest avoiding walking during nighttime and on high speed corridors. However, there is lack of evidence regarding the impact of safety education or training for this group of pedestrians (Duperrex et al., 2002).

In terms of engineering measures, pedestrian crossing should be designed either to be space or time separated from vehicular movement. In terms of space separation, pedestrian crossings should be separated by barrier and fences or off-road or grade-separated facility on high speed corridors and on the roadways with more travel lanes. Several previous studies have demonstrated the safety benefits of such facilities (Elvik et al., 2009; Retting et al., 2003; Berger, 1975). The greater injury severity of pedestrian in the event of crashes with bus and truck further endorse the importance of separating pedestrian traffic from heavy-vehicle traffic flow on roadways. With respect to time separation, pedestrians might be separated from vehicular movement by installation of traffic signal, by implementing exclusive pedestrian signal phase or by installing pedestrian prompting devices (Retting et al., 2002). The implementation of these recommendations will enhance pedestrian safety.

CONCLUSIONS

This paper focuses on identifying the appropriate ordered response structure for modeling pedestrian injury severity. Pedestrian injury severity is often reported as an ordered variable resulting in the application of ordered response models for analyzing risk factors. However, the traditional ordered response model (OL/OP) restrict the impact of risk factors to be the same across all alternatives, thus the model cannot identify risk factors that specifically influence a particular injury category. On the contrary, the generalized ordered logit (GOL) model relaxes the restrictive assumption by allowing for exogenous variable impacts on the threshold parameters in the OL structure. Another ordered response approach, the latent segmentation based ordered logit (LSOL) model, allows for differential impact on the alternatives by segmenting the pedestrian crash population into various segments with segment specific OL parameters. Earlier research efforts have concluded that these approaches are substantially better than the traditional OL model. However, a comparison of these two model frameworks has not been undertaken. Towards this end we undertake a comparison exercise involving four ordered response frameworks: OL, GOL, LSOL with two segments (LSOL II) and LSOL with three segments (LSOL III) to identify the preferred ordered model for examining pedestrian injury severity. The comparison exercise is conducted to identify the various risk factors affecting pedestrian injury severity in terms of model estimation as well as model validation (using a hold-out sample). The empirical analysis is conducted using the “NYC Pedestrian Research Data

Base” for the years of 2002 through 2006. The ordered response models are estimated using a comprehensive set of exogenous variables including: crash characteristics, environmental factors, vehicle characteristics, roadway design and operational attributes, land use characteristics and pedestrian characteristics. The comparison exercise highlights the superiority of the LSOL II model on the estimation sample in terms of data fit compared to the OL and GOL models. In the LSOL approach, pedestrian crashes are assigned probabilistically to two segments – *fatality segment* and *serious injury segment* – based on a host of crash location attributes. The fatality segment is characterized by crashes on high speed roadway facility, mid-block location of road, increased number of travel lanes and decreased number of parking lanes in the roadway system. In the fatality segment, crash during dark-lighted period contribute to increasing the injury severity while snowy/foggy weather, pedestrian age 12 and less and pedestrian age 13 to 18 reduce the injury severity. On the other hand, for the serious injury segment the results indicate that cloudy weather, crash with truck or bus and pedestrian age 65+ increase injury severities while crash during dark-lighted period and spring season are likely to reduce injury severity. Overall, the number of variables moderating the effect of injury severity is higher in the *serious injury segment* compared to the *fatality segment*. Further, some variables provide different impacts, in magnitude as well as in sign, for two segments highlighting how the same variable can have distinct influence on injury severity based on the segment to which the pedestrian is allocated. Thus, target specific countermeasures for “fatality segment” crash locations might ensure an effective reduction of crash related pedestrian fatalities of NYC.

In our research, to further understand the impact of various exogenous factors, elasticity effects for the exogenous variables for both the LSOL and GOL models are computed. The elasticity effects indicate that the most significant variables in terms of fatal injury (from both models) for pedestrians are pedestrian age 65 and above, crash with a truck or bus and crash occurred on a highway or parkway.

The results from the elasticity effects also indicate that there are substantial differences in the elasticity effects of these two models, and these differences might be attributed to the implicit structural differences of these two frameworks. The performance evaluation of these models on a validation sample reveals that GOL model performs marginally better than the LSOL model. The differences in the validation measures at aggregate and disaggregate level are very small for the two frameworks. The improvement in validation predictions for the GOL model is obtained at the cost of six additional parameters. Overall, the comparison exercise supports the hypothesis that both the GOL and LSOL models clearly provide a better fit than standard OL model. The empirical results also show that LSOL model (with six fewer parameters compared to GOL) performance is satisfactory relative to the GOL model performance in the current research context. Further, it is important to reemphasize the fact that LSOL model provides valuable insights on how the explanatory variables affect segmentation of pedestrians into *fatality* and *serious injury* segments. In conclusion, the results from our analysis identify LSOL model as a promising ordered response framework for accommodating population heterogeneity in the context of pedestrian injury severity.

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TABLE 1 Summary of Existing Pedestrian Injury Severity Studies

Paper	Analysis Framework Employed	Pedestrian Injury Severity Representation	Characteristics/Factors Considered					
			Crash	Vehicle	Roadway Design & Land Use	Environment	Pedestrian	Driver
Moudon et al., (2011)	Binary logistic regression	Severely injured/dying, Suffering minor/no injury	---	---	Yes	Yes	Yes	Yes
Tefft, (2013)	Logistic regression	Severe injury, Non-severe injury, Fatal injury, Non-fatal injury	Yes	Yes	Yes	---	Yes	---
Ballesteros et al., (2004)	Logistic regression	Mortality, Non-mortality/Injury severity score <16 and ≥16	---	Yes	Yes	---	---	---
Sze and Wong, (2007)	Binary logistic regression	Killed or severe injury, Slight injury	Yes	---	Yes	Yes	Yes	---
Roudsari et al., (2004)	Multivariate logistic regression	Severe injury, Non-severe injury	---	Yes	Yes	---	Yes	---
Kim et al., (2008b)	Logistic regression	Serious injury, Non-injury	---	---	Yes	Yes	Yes	---
Zajac and Ivan, (2003)	Ordered probit	Fatality, Disabling injury, Not disabling injury, Probable injury, No injury	---	Yes	Yes	Yes	Yes	---
Zahabi et al., (2011)	Ordered logit	No injury, Minor injury, Fatal/Major injury	Yes	Yes	Yes	Yes	---	---
Lee and Abdel-Aty, (2005)	Ordered probit	No injury, Possible injury, Non-incapacitating injury, Incapacitating injury, Fatal injury	---	Yes	Yes	Yes	Yes	---
Clifton et al., (2009)	Generalized ordered probit	No injury, Injury, Fatality	Yes	---	Yes	Yes	Yes	---
Eluru et al., (2008)	Mixed generalized ordered logit, Ordered logit	No injury, Non-incapacitating injury, Incapacitating injury, Fatal injury	Yes	Yes	Yes	Yes	Yes	Yes

Tay et al., (2011)	Multinomial logit	Minor injury, Serious injury, Fatal injury	---	Yes	Yes	Yes	Yes	Yes	Yes
Rifaat et al., (2011)	Multinomial logit	No injury, Injury, Fatality	---	---	Yes	Yes	---	---	Yes
Kim et al., (2008)	Heteroskedastic generalized extreme value logit	Fatal, Incapacitating injury, Non-Incapacitating injury, Possible or No Injury	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aziz et al., (2013)	Random-parameter multinomial logit	Property damage and possible injury, Severe injury, Fatality	Yes	Yes	Yes	Yes	Yes	Yes	---
Kim et al., (2010)	Mixed logit model	Fatal injury, Incapacitating injury, Non-incapacitating injury, Possible/no injury	---	Yes	Yes	Yes	Yes	Yes	Yes
Kwigizile et al., (2011)	Ordered probit, Multinomial logit	No/possible injury, Non-incapacitating injury, Incapacitating injury, Fatal injury	Yes	Yes	Yes	---	Yes	Yes	Yes
Abay, (2013)	Ordered logit, Mixed ordered logit, Multinomial logit, Mixed multinomial logit	Slight/no injury, Serious injury, Fatal injury	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mohamed et al., (2013)	Latent Class Clustering: Ordered probit, K-Means: Multinomial logit	Injury and Fatal injury, No injury, Minor Injury and Fatal injury	---	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 2 Crash Database Sample Statistics

Categorical Explanatory Variables	Sample Share	
	Frequency	Percentage
<i>Crash Location</i>		
At intersection	3079	72.31
At mid-block	1179	27.69
<i>Weather Condition</i>		
Snowy/Foggy	47	1.10
Clear	3061	71.89
Cloudy	555	13.03
Rain	595	13.97
<i>Season</i>		
Winter	1041	24.45
Spring	1024	24.05
Summer	1060	24.89
Autumn	1133	26.61
<i>Light Conditions</i>		
Daylight	2396	56.27
Dawn	100	2.35
Dusk	195	4.58
Dark road - lighted	1518	35.65
Dark road - unlighted	49	1.15
<i>Vehicle Type</i>		
Other vehicle type	827	19.42
Car/van/pickup	3155	74.10
Truck	140	3.29
Bus	106	2.49
Motorcycle	30	0.70
<i>Roadway Class</i>		
Town	15	0.35
Urban street	4125	96.88

Parkway	35	0.82
Parking lot & other non-traffic	52	1.22
Highway	31	0.73
<i>Land use</i>		
Family residential	729	17.12
Mixed residential and commercial	403	9.46
Commercial and office	752	17.66
Industrial / Manufacturing	953	22.38
Open Space & Vacant Land	426	10.00
Parking Facilities and Transportation Utility	750	17.61
Public facilities and institutions	153	3.59
Misc. lots	92	2.16
<i>Boroughs</i>		
Bronx	661	15.52
Brooklyn	1408	33.07
Manhattan	1178	27.67
Queens	848	19.92
Staten island	163	3.83
<i>Pedestrian Age</i>		
Children (Pedestrian age 12 and less)	612	14.37
Teenager (Pedestrian age 13 to 18)	378	8.88
Adult (Pedestrian age 19 to 65)	2521	59.21
Older (Pedestrian age 65+)	747	17.54
Ordinal Explanatory Variables		Mean
Travel lane	2.030	
Parking lane	1.420	

TABLE 3 Measures of Fit in Estimation Sample

Summary Statistic	OL	GOL	LSOL II
Log-likelihood at zero	-4677.9	-4677.9	-4677.9
Log-likelihood at sample shares	-1654.5	-1654.5	-1654.5
Log-likelihood at convergence	-1481.6	-1454.5	-1456.19
Number of parameters	20	22	16
Number of observations	4258	4258	4258
BIC	3120.1	3092.8	3046.1
AICc	3007.5	2953.2	2944.5
Adjusted likelihood ration index ($\bar{\rho}_2^2$)	0.092	0.108	0.110

OL = Ordered logit model; GOL = Generalized ordered logit model; LSOL II = Latent segmentation based ordered logit model with two segment; BIC = Bayesian Information Criterion; AICc = Akaike Information Criterion corrected.

TABLE 4 Latent Segmentation based Ordered Logit Model with Two Segments (LSOL II) Estimates

		Segments			
		Segment 1		Segment 2	
Injury severity	Pedestrian population share	0.11		0.89	
	Property damage only (PDO)/	6.07		0.84	
	Minor Injury	49.13		93.82	
	Serious Injury	44.80		5.34	
PARAMETER ESTIMATES					
Explanatory Variables		Segment 1		Segment 2	
		Estimate	t-stat	Estimate	t-stat
<i>Segmentation Components</i>					
<i>Constant</i>		--	--	3.0813	7.4560
<i>Regional country (Ref: Bronx, Brooklyn, Queens)</i>					
Manhattan		--	--	0.5560	2.1420
Staten island		--	--	-0.8659	-1.8810
<i>Functional class of roadway (Ref: Urban Street)</i>					
Highway and Parkway		--	--	-2.6484	-3.9940
<i>Pedestrian location (Ref: Pedestrian at intersection)</i>					
Pedestrian at mid-block		--	--	-1.2367	-5.0650
<i>Travel lane</i>		--	--	-0.4107	-4.6530
<i>Parking lane</i>		--	--	0.2940	2.4460
<i>Injury Severity Components</i>					
<i>Threshold parameters</i>					
Threshold 1		-2.8668	--	-4.8333	--
Threshold 2		0.4893	--	3.9953	--
<i>Weather condition (Ref: Clear and Rain)</i>					
Snowy/Foggy		-3.9723	-2.6350	--	--
Cloudy		--	--	0.5210	2.1540
<i>Light conditions (Ref: Daylight)</i>					
Dark road - lighted		1.4309	2.3580	-0.4675	-1.7630
<i>Vehicle type (Ref: Car/van/pickup)</i>					
Truck		--	--	2.5982	8.0080
Bus		--	--	2.1061	5.7110
<i>Pedestrian age (Ref: Adult)</i>					
Children		-0.7475	-1.6760	--	--
Teenager		-1.3881	-2.6140	--	--
Older		--	--	2.4296	7.5770
<i>Season (Ref: Winter, Summer, Autumn)</i>					
Spring		--	--	-0.5052	-2.2530

TABLE 5 Elasticity Effects

Variables	LSOL II			GOL		
	PDO/ Minor injury	Serious injury	Fatal injury	PDO/ Minor injury	Serious injury	Fatal injury
Manhattan	-16.05	2.22	-18.25	34.67	2.24	-25.31
Staten island	36.22	-4.83	39.51	-36.54	-4.03	42.04
Highway	167.058	-22.153	181.128	628.96	-24.28	134.67
Parkway	167.058	-22.153	181.128	-75.58	-17.78	173.39
Pedestrian at mid-block	46.58	-6.39	52.48	56.72	-7.08	56.95
Travel lane	15.25	-2.03	16.61	0.00	-2.31	21.13
Parking lane	-8.58	1.15	-9.42	15.88	1.02	-11.52
Snowy/Foggy	466.79	-2.08	-48.48	173.41	3.89	-59.79
Cloudy	-22.98	-2.07	22.53	-37.81	-3.86	40.65
Dark-lighted	-18.20	-1.81	19.46	0.00	-4.14	37.94
Dark-unlighted	--	--	--	343.97	-17.92	116.14
Truck	-51.23	-22.09	212.26	-86.55	-26.15	251.52
Bus	-47.82	-15.46	150.28	0.00	-18.60	170.27
Pedestrian age 12 and less	35.60	1.28	-17.02	39.60	2.27	-26.32
Pedestrian age 13 to 18	83.70	1.85	-29.32	89.59	3.64	-45.81
Pedestrian age 65+	-57.75	-14.57	143.44	-83.96	-14.87	147.89
Spring	30.52	1.42	-17.61	24.51	1.62	-18.22
Industrial and Vacant land	--	--	--	73.27	0.17	-11.75

LSOL II = Latent segmentation based ordered logit model with two segments; GOL = Generalized ordered logit model; PDO = Property damage only.

TABLE 6 Measures of Fit in Validation Sample

DISAGGREGATE MEASURE OF FIT IN VALIDATION SAMPLE				
Summary statistic		GOL	LSOL II	
Number of observations		443	443	
Predictive Log-likelihood		-168.43	-168.94	
Average probability of correct prediction		88.49	83.30	
Average probability for chosen probability>0.70		83.97	85.78	
AGGREGATE MEASURE OF FIT IN VALIDATION SAMPLE				
Injury categories/Measures of fit		Actual shares	GOL predictions	LSOL II predictions
	PDO/ Minor injury	1.80	1.39	1.47
	Serious injury	88.90	88.86	88.12
	Fatal injury	9.30	9.75	10.41
	RMSE	-	0.30	0.70
	MPAE	-	6.89	7.82
	Manhattan	PDO/ Minor injury	1.60	1.59
Serious injury		87.70	89.55	88.56
Fatal injury		10.70	8.86	10.05
RMSE		-	10.78	10.20
MPAE		-	11.73	10.98
Predictive Log-likelihood		-	-52.98	-52.65
Cloudy	PDO/ Minor injury	3.2	0.99	1.22
	Serious injury	88.9	88.13	89.12
	Fatal injury	7.9	10.87	9.66
	RMSE	-	16.75	16.45
	MPAE	-	32.82	33.95
	Predictive Log-likelihood	-	-27.76	-28.80
Dark road – lighted	PDO/ Minor injury	3.1	1.42	1.48
	Serious injury	86.3	87.81	87.44
	Fatal injury	10.6	10.77	11.08
	RMSE	-	27.30	27.04
	MPAE	-	37.96	38.26
	Predictive Log-likelihood	-	-79.29	-77.10
Pedestrian age 12 and less	PDO/ Minor injury	1.5	1.76	1.86
	Serious injury	95.5	93.64	93.35
	Fatal injury	3.0	4.61	4.80
	RMSE	-	16.38	16.48
	MPAE	-	14.70	14.68
	Predictive Log-likelihood	-	-13.36	-14.15
Spring	PDO/ Minor injury	0.9	1.66	1.65
	Serious injury	92.0	89.86	89.69
	Fatal injury	7.1	8.48	8.65
	RMSE	-	4.95	4.89
	MPAE	-	38.40	38.89
	Predictive Log-likelihood	-	-32.41	-32.76

GOL = Generalized ordered logit model; LSOLII = Latent segmentation based ordered logit model with two segments; PDO = Property damage only; RMSE = Root mean square error; MPAE = Mean absolute percentage error.