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A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes

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ABSTRACT: This paper proposes an econometric structure for injury severity analysis at the level of individual accidents that recognizes the ordinal nature of the categories in which injury severity are recorded, while also allowing flexibility in capturing the effects of explanatory variables on each ordinal category and allowing heterogeneity in the effects of contributing factors due to the moderating influence of unobserved factors. The model developed here, referred to as the mixed generalized ordered-response logit (MGORL) model, generalizes the standard ordered-response models used in the extant literature for injury severity analysis. To our knowledge, this is the first such formulation to be proposed and applied in the econometric literature in general, and in the safety analysis literature in particular. The MGORL model is applied to examine non-motorist injury severity in accidents in the USA, using the 2004 General Estimates System (GES) database. The empirical findings emphasize the inconsistent results obtained from the standard ordered response model. An important policy result from our analysis is that the general pattern and relative magnitude of elasticity effects of injury severity determinants are similar for pedestrians and bicyclists. The analysis also suggests that the most important variables influencing non-motorist injury severity are the age of the individual (the elderly are more injury-prone), the speed limit on the roadway (higher speed limits lead to higher injury severity levels), location of crashes (those at signalized intersections are less severe than those elsewhere), and time-of-day (darker periods lead to higher injury severity).

KEY WORDS: ***Injury severity, ordered-response model, pedestrian safety, bicyclist safety, non-motorized travel.***

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1. Introduction

Traffic congestion levels in metropolitan areas of the United States have risen substantially over the past decade (see Shrank and Lomax, 2005). This has been, in large part, because of the increasing dependency on the personal automobile for pursuing out-of-home work and non-work activities. For instance, the 2001 NHTS data shows that about 92% of US households owned at least one motor vehicle in 2001 (compared to about 80% in the early 1970s; see Pucher and Renne, 2003). Household vehicle miles of travel also increased 300% between 1977 and 2001 (relative to a population increase of 30% during the same period; see Polzin and Chu, 2004).

In response to the rising personal vehicle-based travel trends, and the concomitant traffic congestion and associated air quality problems, several metropolitan planning organizations are considering, among other things, transportation demand management strategies to encourage non-motorized mode use, including walking and bicycling for short distance utilitarian trips. In addition to serving as a potential traffic congestion alleviation strategy, promoting non-motorist travel (or active transportation) also provides health and fitness benefits, net of exposure to air pollutants emitted by cars, an issue that is receiving increasing attention at the interface of transportation and public health (see, for example, Transportation Research Board and Institute of Medicine, 2005, Sallis *et al.,* 2004, and Copperman and Bhat, 2006).

To be sure, a significant fraction of trips in US urban areas are short-distance trips that can be undertaken by walking or bicycling. According to evidence from the 2001 National Household Travel Survey (NHTS), 41% of all trips in 2001 were shorter than 2 miles and 28% were shorter than 1 mile (Pucher and Renne, 2003). However, Americans used their personal vehicles for about 90% of trips between 1 and 2 miles, and about 66% of trips shorter than 1 mile. While there are several reasons for this dominance of the automobile even for short distance trips, safety (or the lack thereof) associated with non-motorized mode use in the US is an important consideration. The US has a notoriously poor safety record relative to other developed countries. According to a study by Pucher and Dijkstra (2003), after controlling for travel exposure in terms of mileage, US pedestrians (cyclists) are roughly 3 times (2 times) more likely to get killed in traffic accidents than German pedestrians (cyclists) and over 6 times (3 times) more likely than Dutch pedestrians (cyclists). Pucher and Dijkstra also compared fatality rates per mile of travel by different modes in the US, and concluded that pedestrians were 23 times more likely to get killed than car occupants, and bicyclists were 12 times more likely. In terms of absolute numbers, traffic crashes led to 4,881 pedestrian fatalities and 784 bicyclist fatalities in 2005 (Traffic Safety Facts, NHTSA 2005). In addition, 110,000 pedestrians and bicyclists were injured in traffic crashes in the same year. Overall, these statistics indicate that, on average, a non-motorist is killed every 93 minutes and one is injured every 5 minutes in traffic accidents in the US.

The high risk of pedestrian and bicyclist injuries/fatalities in the US has led to increased attention in the past decade on traffic accidents involving non-motorists (earlier safety research focused primarily on vehicle occupants). Researchers have examined a host of different risk factors associated with non-motorized mode-related accident rates and injury severity to improve motorized vehicle and roadway design, enhance control strategies at conflict locations, design good bicycle and pedestrian facilities, and formulate driver and non-motorized user education programs. The risk factors considered in earlier studies have included one or more of the following categories of variables: (1) pedestrian/bicyclist characteristics (such as age, gender, helmet use, alcohol consumption), (2) motorized vehicle driver characteristics (such as state of soberness and age), (3) motorized vehicle attributes (such as vehicle type and speed), (4) roadway characteristics (such as speed limit and whether the highway is divided or not) (5) environmental factors (such as time of day, day of week, and weather conditions), and (6) crash characteristics (such as the direction of impact and motorist/non-motorist maneuver type at impact).

In this paper, the objective is to contribute to the literature on the risk factors identified above that are associated with injury severity of non-motorists in traffic accidents. In doing so, our emphasis is on undertaking the analysis at the level of individual accidents, and simultaneously examining the effects of the multidimensional set of potentially contributing factors. The analysis is conditioned on a crash between a motorized vehicle and a non-motorist; that is, the focus is on the characteristics that impact non-motorized user injury severity given that a crash occurred (in the rest of this paper, we will use the term “crash” and ‘accidents” interchangeably to refer to an incident involving a non-motorist and a motorized vehicle). We adopt the “conditioned-on-crash” approach so that we can rigorously model the effects of contributing factors at the disaggregate level of each crash, while also obviating the need to have a measure of exposure. Most earlier research studies, on the other hand, have examined accident risk at an aggregate level by analyzing the total number of accidents of each injury type as a function of various contributing factors (such as sex and age of pedestrian/bicyclist, and vehicle type).

The rest of this paper is structured as follows. Section 2 discusses relevant earlier research studies and positions the current study. Section 3 provides details of the methodology used in the current study to examine non-motorist user injury severity. Section 4 describes the data source employed and the sample formation procedures. Section 5 presents the empirical estimation results and their implications for reducing non-motorized user injury severity in crashes. Finally, Section 6 summarizes the major results and identifies the study limitations.

2. The Current Study in Context

2.1 Earlier Research

There is a vast body of safety literature examining the factors affecting crash occurrence of non-motorized road users (pedestrians and bicyclists) and the frequency of different types of non-motorized crashes with motorized vehicles. For example, Garder (2004) examines pedestrian crash data from Maine, and finds that pedestrian crashes are more prevalent on Saturdays, in the afternoons between 4 and 7 pm, at times of clear weather, on level, straight, roads, and at locations without any traffic control devices or signage (this study did not control for exposure). Some other studies have examined the characteristics of fatal crashes involving pedestrians and bicyclists. For instance, Harruff (1998) undertook a descriptive analysis of pedestrian traffic fatalities in Seattle and found a lower proportion of individuals aged 22-34 years, females, and Caucasians (relative to the representation of these groups in the overall population) in the "fatal" sample. Harruff also examined the time of day, the day of week, the season of year, the characteristics of the crash location, effect of alcohol, type of vehicles involved, and body place of injury in the "fatal" sample (see also Garder, 2004 for a similar analysis). In the rest of this section, we do not discuss studies such as those identified above that focus on crash occurrence/frequency or that focus on an aggregate level analysis of the characteristics of solely fatal crashes. We also do not examine studies attempting to measure pedestrian and bicyclist exposure data (see Jonah and Engel, 1983, Malek *et al.,* 1990, Keall, 1995, Carlin *et al.,* 1995, or Hall and Kaltnecke, 1999 for exposure studies). Rather, we limit ourselves strictly to crash-level studies that examine non-motorist injury severity in accidents involving a non-motorist and a motorized vehicle.

The studies examining injury severity in traffic crashes involving non-motorized road users with motorized vehicles may be broadly classified into two categories, depending on the level at which the analysis is undertaken. One group of studies aggregates crashes by non-motorized road user injury severity level, and compares the non-motorized user, driver, vehicle, roadway, environmental, and crash characteristics across the various categories of injury severity level. We characterize these as descriptive analyses, since they are based on univariate or bivariate associations at an aggregate level. A second group of studies pursues a multivariate analysis of the factors affecting injury severity at the level of individual accidents. We characterize these as multivariate models.

Table 1 provides a summary of previous descriptive analysis studies, while Table 2 provides a summary of multivariate model studies (within each table, the studies are organized chronologically). These tables provide information on the non-motorist user type considered (pedestrians, bicyclists, or both), the injury severity representation (*i.e.*, the dependent variable in the analysis), the data source used, the analysis framework employed, the independent variable categories considered in the analysis (from the six categories of non-motorist characteristics, motorized vehicle driver characteristics, motorized vehicle attributes, roadway characteristics, environmental factors, and crash characteristics), and the summary findings (by independent variable category). Three general observations may be made from these tables. First, the field is seeing a movement toward multivariate analysis and away from the descriptive analysis used in the studies undertaken in the more distant past. Among the multivariate modeling approaches (see Table 2), the logistic regression has been widely used when the injury severity representation is in a binary form (such as fatal versus non-fatal injury), while the ordered-response model has been commonly used when the injury severity representation is recorded in multiple categories (such as property damage only, no visible injury but pain, non-incapacitating injury, incapacitating injury, and fatal injury). The use of the ordered-response model when injury severity levels are collected in multiple categories is not surprising, since the resulting dependent variable is intrinsically discrete and ordinal. Second, all earlier studies in Tables 1 and 2 have examined either pedestrian or bicyclist injury severity, but not both. This precludes a comparison of the similarities and differences in the factors, and the magnitude of the impact of factors, affecting injury severity between the two non-motorist user groups. Third, earlier studies have in the main considered non-motorist characteristics as a determinant variable category for non-motorist injury severity (see the column labeled "Categories of Independent Variables Considered" in the tables). As suggested by Al-Ghamdi (2002), the inclusion of non-motorist characteristics appears to be based on the traditional view that non-motorists decide their own "safety destiny" based on their personal factors. In contrast, few studies have considered the attributes of the driver of the motorized vehicle, even though there is a clear acknowledgement that, more often than not, it is the driver of the motorized vehicle who is at fault (see Insurance Institute for Highway Safety, 1999 and Ballesteros *et al.,* 2004). Overall, only two studies (Pitt *et al.,* 1990; Kim *et al.,* 2007) appear to have considered variables relating to all the six variable categories identified earlier.

Tables 1 and 2 also provide summary findings from earlier studies regarding the factors that have been found to impact injury severity (see the last column). Overall, studies analyzing pedestrian injury severity indicate that pedestrians who are male, intoxicated, and very young or elderly are more prone to severe injuries, as are pedestrians struck by an alcohol-intoxicated driver, by non-sedan vehicles (SUVs, pick-up vans), and by high speed vehicles. Pedestrian injuries in crashes at school zone locations, on higher speed-limit roads, on two-way roads with median, and in residential and rural areas increase injury severity. Pedestrian-motor vehicle crashes occurring during the night time and in adverse weather conditions increase the likelihood of being fatally injured, as also do frontal collisions. Studies examining factors that influence bicyclist injury severity are much fewer, but indicate that bicyclists who are intoxicated and elderly (> 50-55 years), hit by an alcohol-intoxicated motorist, struck by a speeding or heavy vehicle, and involved in accidents at high speed limit, low traffic volume and curved/non-flat roadway locations tend to be more severely injured. Also, bicyclist-related crashes occurring in conditions of darkness with no lighting, in inclement weather (fog, rain and snow) and in the morning peak period lead to more severe bicyclist injuries. Interestingly, the two studies of bicyclist injury severity that include crash characteristics (Stone and Broughton, 2003 and Kim *et al.,* 2007) appear to provide inconsistent results with respect to the effect of the direction of impact, with one study suggesting that back impacts are more severe than front or side impacts, and the other indicating that head-on collisions are more severe than other directions of impact.

2.2 The Current Research

The overview of the literature in the previous section indicates that, increasingly, the studies of non-motorized user injury severity have used a multivariate modeling approach. Within the multivariate modeling approach, the method of choice for modeling non-motorized injury severity when it is recorded in multiple categories is the ordered-response framework, which recognizes the ordinal and discrete nature of injury severity (e.g., none, possible, non-incapacitating, incapacitating injury and fatality). Recent studies have also begun to recognize a range of explanatory variables to explain injury severity. The current research adds to this literature on non-motorized injury severity in several ways. First, we use a multivariate modeling approach that generalizes the ordered response model structure used in earlier studies. The generalization, which we refer to as the generalized ordered logit model, adds flexibility in capturing the effects of explanatory variables on the ordinal categories of injury severity, especially in the treatment of the utility thresholds, thus removing strong restrictions imposed by the ordered response logit models used in the extant literature. Second, our study examines the effects of factors on injury severity levels for pedestrians *and* bicyclists, allowing us to compare the magnitude of the effects of contributing factors between the two non-motorized road user groups. Third, we include a comprehensive set of contributing factors in our study to explain injury severity, including non-motorist, driver, vehicle, roadway, environmental, and crash characteristics. Finally, we allow heterogeneity in the effects of injury severity determinants due to the moderating influence of unobserved factors. For instance, the slower reaction time of being intoxicated may be exacerbated by the use of a walkman. But accident reports may not record or may miss information on walkman use and so walkman use may be unobserved. Ignoring the moderating effect of such unobserved variables can, and in general will, result in inconsistent estimates in nonlinear models (see Chamberlain, 1980 and Bhat, 2001).

3. Econometric Framework

The previous section indicated the increasing use of the ordered-response structure to model injury severity when it is recorded in multiple ordinal categories. The ordered-response structure is based on the notion of a latent underlying injury risk propensity occurring from a crash that determines the observed ordinal injury severity level. Specifically, a low value on the latent injury risk propensity is associated with a lower observed injury severity level, while a high value on the propensity scale is associated with a fatal incident. Intermediate propensity values lead to intermediate injury severity levels. The threshold values on the propensity scale that demarcate the observed injury severity categories are parameters that are estimated in the analysis. Essentially, then, the ordered-response structure corresponds to an ordered partitioning of the real line into the observed injury severity categories. The latent propensity is specified as the sum of a linear-in-parameters deterministic component (which is a function of relevant injury severity determinants) and a random component (that represents the effects of unobserved attributes of each crash). The econometric specification of the ordered-response structure is completed by assuming a particular continuous probability density function for the random component. The two most common assumptions for the density function correspond to the normal distribution (leading to the ordered-response probit model) and the logistic distribution (leading to the ordered-response logit model). Both the ordered-response probit and ordered-response logit models are easy to estimate and provide essentially identical results (see Bhat and Pulugurtha, 1998).

In the rest of this section, we present the notational formulation for the standard ordered-response logit form (ORL) as described above and used in earlier studies of non-motorized injury severity. We also identify the limitations of this standard formulation (Section 3.1). Subsequently, we present the mixed generalized ordered response logit model (MGORL) structure used in the current study, and the technique to estimate this model (Section 3.2).

3.1 The Standard Ordered Response Model and its Limitations

Let q (q = 1, 2, …, Q) be an index to represent non-motorists and let k (k = 1, 2, 3, …, K) be an index to represent injury severity. The index k, for example, may take values of "No injury" (k=1), "Possible injury" (k=2), "Non-incapacitating injury" (k = 3), "Incapacitating injury" (k = 4), and "Fatal injury" (k = 5). The equation system for the standard ordered response logit (ORL) model is (see McElvey and Zavoina, 1978, who first proposed the ORL model):

$$y_q^* = \beta' x_q + \varepsilon_q,\ y_q = k \text{ if } \psi_{k-1} < y_q^* < \psi_k \tag{1}$$

where y_q^* corresponds to the latent injury risk propensity for non-motorist q in the crash she or he was involved in. x_q is an (L x 1)-column vector of attributes (excluding a constant) associated with the non-motorist, driver, vehicle, roadway, environment, and crash characteristics of the crash involving individual q. β is a corresponding (L x 1)-column vector of variable effects. The latent propensity y_q^* is mapped to the observed injury severity level y_q by the ψ thresholds ($\psi_0 = -\infty$ and $\psi_K = \infty$) in the usual ordered-response fashion. It is important to note that the model structure requires the ψ thresholds to be strictly ordered for the partitioning of the latent risk propensity measure into the observed ordinal injury severity categories (*i.e.*, $-\infty < \psi_1 < \psi_2 < \ldots < \psi_{K-1} < \infty$). ε_q is an idiosyncratic random error term that impacts injury risk propensity and may include, for example, the overall fitness level or alertness level of the non-motorist. ε_q is assumed to be identically and independently standard logistic distributed across individuals q.[1]

The ORL model allows non-linear effects of any variable on the probabilities of sustaining different levels of injury severity. For example, the effect of being intoxicated (relative to being sober) may dramatically reduce the probability of not being injured at all, reduce to a lesser degree the probability of some injury, have no effect on the probability of non-capacitating injury, and substantially increase the probability of a capacitating or fatal injury. This is because of the non-linear mapping of the risk propensity function to the observed injury severity levels, through the threshold values and the assumed distribution of the random error term ε_q. However, a limitation of the ORL model is that it holds the threshold values to be fixed across crashes. This can lead to inconsistent (*i.e.,* incorrect) estimates of the effects of variables. To illustrate this, consider two groups of crashes. The first group of crashes involves intoxicated motorists who hit bicyclists sideways. The second group involves sober motorists who hit bicyclists head-on. Assume, solely for ease in presentation, that being hit by an

1 The exclusion of a constant in the vector x_q of equation (1) is an innocuous normalization as long as all the intermediate thresholds (ψ_1 through ψ_{K-1}) are left free for estimation. Similarly, the use of the standard logistic distribution rather than a non-standard logistic distribution for the error term is also an innocuous normalization (see Bhat, 1991 and Bhat and Koppelman, 1993).

intoxicated versus sober driver and being hit head-on versus sideways are the only variables included in the bicyclist injury severity model. Let the coefficients on these variables in the latent injury risk propensity equation be +0.25 (for the motorist being under the influence of alcohol relative to being sober) and +0.25 (for being hit head-on rather than sideways). Since there are unobserved factors across crashes within each group, the injury risk propensity within each group takes a mean value of +0.25 and is distributed standard logistic. This is shown in Figure 1. Let the thresholds values be fixed across crashes at ψ_1= -1.5, ψ_2= -0.25, ψ_3= 0.5, and ψ_4= 1.25. Then, for each of the two crash groups, the predicted probabilities of each injury severity level are (observed as areas of the logistic curve between appropriate thresholds): No injury (0.15), possible injury (0.23), non-incapacitating injury (0.18), incapacitating injury (0.17) and fatal injury (0.27). However, the reality may be that the crashes in the first group involving an intoxicated motorist load much more on the incapacitating injury and fatal injury categories for the bicyclist, while there is no difference between the two crash groups for the "no injury" and "possible injury" categories. This cannot be reflected by the ORL model because the thresholds are fixed across individuals. However, if the thresholds are allowed to vary across crashes, so that ψ_3= 0.5 – 0.5 * (intoxicated bicyclist involved) and ψ_4= 1.25 – 0.25 * (intoxicated bicyclist involved), the loading toward the higher injury severity categories for the crashes with an intoxicated motorist can be reflected. This situation is depicted in Figure 2. The thresholds now are ψ_1= -1.5, ψ_2= -0.25, ψ_3= 0, and ψ_4= 1.00. The probabilities for the intoxicated crashes are: No injury (0.15), possible injury (0.23), non-incapacitating injury (0.06), incapacitating injury (0.24) and fatal injury (0.32).

The example above is a simple illustration of the restriction imposed by the ORL model. In reality, there will be several variables impacting injury risk propensity, and several variables potentially influencing the thresholds. The important point to note is that imposing the restriction of fixed thresholds across crashes will, in general, lead to inconsistent injury risk propensity and threshold values, and inconsistent effects of variables on the likelihood of different categories of injury severity.

3.2 The Mixed Generalized Ordered Response Logit (MGORL) Model

The MGORL model allows the thresholds in the ORL model to vary based on both observed as well as unobserved characteristics. The model proposed here builds on the earlier work of Terza (1985) and Srinivasan (2002), but is different from these earlier studies in that it adopts a functional specification that immediately guarantees the ordering of the thresholds (*i.e.*, $-\infty<$ ψ_1 $<\psi_2$ < …< $\psi_{K-1}<\infty$) for each and every individual *q*. It also accommodates unobserved heterogeneity in the effect of exogenous variables on injury propensity and the threshold values.

The next section presents the MGORL model structure, while Section 3.2.2 discusses the estimation procedure.

3.2.1 The MGORL Model Structure

The starting point for the MGORL model is Equation (1), except that the β vector and the ψ thresholds are now subscripted by the index *q* to reflect that these parameters can vary across crashes of different individuals due to observed and unobserved factors.

$$y_q^* = \beta_q' x_q + \varepsilon_q, \; y_q = k \text{ if } \psi_{q,k-1} < y_q^* < \psi_{q,k} \tag{2}$$

Next, we adopt a specific parametric form for the thresholds to guarantee the ordering conditions ($-\infty < \psi_{q,1} < \psi_{q,2} < \ldots < \psi_{q,K-1} < \infty$) for each crash *q*. To do so, we write:

$$\psi_{q,k} = \psi_{q,k-1} + \exp(\alpha_{qk} + \gamma'_{qk} z_{qk}), \tag{3}$$

where z_{qk} is a set of exogenous variables associated with the k^{th} threshold (excluding a constant), γ_{qk} is a corresponding crash-specific vector of coefficients, and α_{qk} is a parameter associated with injury severity level $k = 1, 2, \ldots K-1$. For identification reasons, we adopt the normalization that $\psi_{q,1} = \exp(\alpha_1)$ for all *q* (this is innocuous as long as the vector x_q is included in the risk propensity equation). Finally, to allow heterogeneity in the effects of relevant exogenous variables on the latent injury risk propensity (as discussed in Section 2.2), and to allow unobserved heterogeneity effects of variables on the threshold values, we consider the β_q and θ_q vectors (the θ_q vector is formed by vertically stacking all the γ_{qk} vectors and the α_{qk} scalars across all *k*) as realizations from multivariate normal distributions $\phi(\beta)$ and $\phi(\theta)$, respectively[2].

The MGORL model is a generalized version of the ORL model. Specifically, the ORL model imposes the restrictions that (a) $\beta_q = \beta$ for all *q* (b) γ_{qk} =0 for all *q* and *k*, and (c) α_{qk} collapses to a fixed point for all *q* and for each *k* = 1,2,...*K*-1. Thus, one can test the validity of the restrictions imposed by the restrictive ORL model using nested likelihood tests after estimating the MGORL model.

3.2.2 The MGORL Model Estimation

Let *G*(.) be the cumulative distribution of the standard logistic distribution and let d_{qk} be a dummy variable taking the value 1 if the non-motorist *q* sustains an injury of level *k* and 0 otherwise. Then, the likelihood function for the q^{th} individual may be written as:

[2] Note, however, that the α_{q1} scalar in θ_q is held fixed across all *q* for identification reasons ($\alpha_{q1} = \alpha_1$ for all *q*).

$$L_q = \int\limits_{\beta}\int\limits_{\theta} \left\{ G\left[(\psi_{qk} \mid \theta) - \beta' x_q \right] - G\left[(\psi_{qk} \mid \theta) - \beta' x_q \right] \right\}^{d_{qk}} \phi(\beta)\,\phi(\theta)\, d\beta\, d\theta \qquad (4)$$

The corresponding log-likelihood function is:

$$L = \sum_q \ln L_q \qquad (5)$$

The parameters to be estimated in the MGORL model are the moment parameters (mean and covariance matrix) of the multivariate distributions of β and θ. These can be obtained by maximizing the log-likelihood function of Equation (5) with respect to the moment parameters. The log-likelihood involves a multidimensional integral whose dimensionality is determined by the number of random components in the β and θ vectors. In the current paper, we used Halton draws to evaluate the multidimensional integrals (see Bhat 2001, 2003).

4. Data

The data is sourced from the 2004 General Estimates System (GES) obtained from the National Highway Traffic Safety Administration's National Center for Statistics and Analysis. The GES consists of data compiled from a sample of police-reported accidents that involve at least one motor vehicle traveling on a traffic way and resulting in property damage, injury, or death. The GES data are drawn from accidents in about 60 areas across the U.S. that reflect the geography, population, and traffic density of the U.S. (see http://www-nrd.nhtsa.dot.gov/departments/nrd-30/ncsa/ges.html for comprehensive details of how the accident reports are collected and compiled). The 2004 GES includes information on 60,000 accidents involving about 150,000 individuals and 100,000 vehicles. Of these about 3,200 accidents involved non-motorists.

A number of accident-related attributes are collected for each accident in the GES, including the characteristics of the individuals involved, vehicle characteristics, roadway design attributes, environment factors, and crash characteristics. The injury severity of each individual involved in the accident is collected on a five point ordinal scale: (1) No injury, (2) Possible injury, (3) Non-incapacitating injury, (4) Incapacitating injury, and (5) Fatal injury.

4.1 Sample Formation and Description

The focus of this analysis is on accidents that involve pedestrians or bicyclists. Further, we confined our attention to accidents involving a single motorized vehicle and a single non-motorist. Such accidents constitute 92% of all accidents involving pedestrians or bicyclists in the GES data.

The final sample of accidents in the current analysis consisted of 2,944 records. The distribution of non-motorist injury severity by type of non-motorist (pedestrians or bicyclists) is presented in Table 3. In this table, the injury severity categories of no injury and possible injury are combined into a single category because of the extremely low number of crashes in which the non-motorist was not injured (we will refer to this combined category as "no injury" in the rest of this paper). The descriptive statistics in Table 3 indicate a substantially higher percentage of pedestrians than bicyclists who are likely to be seriously or fatally injured. Overall, about 30% of motorized vehicle crashes with a non-motorist result in serious injury or death to non-motorist.

Table 4 presents the distribution of injury severity by whether or not the non-motorist was alcohol-intoxicated. The results clearly show a positive correlation between alcohol intoxication and injury severity level. As we will see later, this positive correlation remains even after controlling for several other variables in the multivariate MGORL model.

5. Empirical Analysis

5.1 Variables Considered

Several types of variables were considered in the empirical analysis, including non-motorist characteristics, motorized vehicle driver characteristics, motorized vehicle attributes, roadway characteristics, environmental factors, and crash characteristics. The <u>Non-motorist and motorized vehicle driver characteristics</u> included demographics (age and sex) and alcohol consumption. The only <u>motorized vehicle attribute</u> included in the current study is the vehicle type involved in the crash. The vehicle types considered include passenger cars, sports utility vehicles, pick up trucks, and vans (the final category groups minivans, full vans, and other van types in a single category). Other vehicle attributes, such as vehicle weight and vehicle speed just before impact, are either not available in, or missing for a large fraction of, the GES data. The <u>roadway characteristics</u> considered in the analysis are speed limit and the type of regulatory signs/ control at the accident location (*i.e.* whether the accident occurred at a location with stop signs, warning signs, regulatory signs, traffic signals, or no signs). Again, additional roadway characteristics, such as number of lanes, alignment of roads, and grade and shoulder widths, could not be included because of the absence of data, or the large fraction of missing data, on these variables in the GES. <u>Environmental factors</u> related to the crash included day of the week, time of day represented in three categories (day time - 6am to 6 pm, evening - 6pm to midnight, and late night - midnight to 6am), lighting conditions (dawn, daylight, dusk, dark, and dark and lit), and weather conditions (no adverse weather, rain, snow, and fog). Finally, the <u>crash characteristics</u> included the direction of impact of the vehicle and the non-motorist (front, sideways, or other).

In addition to the variables identified above, we also considered several interaction effects among the variables from the six variable categories. Further, we tested for the differential impact of all these variables on pedestrian and bicycle injury severity levels. The final specification was based on a systematic process of removing statistically insignificant variables and combining variables when their effects were not significantly different. The specification process was also guided by prior research and intuitiveness/parsimony considerations. For the continuous variables in the data (such as age and speed limits), we tested alternative functional forms that included a linear form, a spline (or piece-wise linear) form, and dummy variables for different ranges.

5.2 Estimation Results

We estimated two different models in the research effort: (1) a standard ordered response logit (ORL) model that has been extensively used in the non-motorized injury severity analysis literature, as discussed in Section 2, and (2) the mixed generalized ordered response logit (MGORL) model that generalizes the ORL model. In both models, the dependent variable included four ordinal levels of injury severity: (1) no injury or possible injury, which we will simply refer to as "no injury" for brevity (2) non-incapacitating injury, (3) incapacitating injury and (4) fatal injury.

In the following presentation of the empirical results, we first discuss the model parameter estimates of the best specification of the MGORL model, which was obtained after extensive specification testing (Section 5.2.1). Next, we present and compare the implied elasticity effects of variables on the observed injury severity categories between the ORL model and the MGORL model (Section 5.2.2). Finally, various fit measures are defined and used to assess the relative predictive performance of the ORL and the MGORL models (Section 5.2.3).

5.2.1 MGORL Estimation Results

The structure of the MGORL model, as developed in Section 3, does not include a constant in the latent injury risk propensity equation. However, there is a threshold identified between the first and second ordinal categories of no injury and non-incapacitating injury (*i.e.*, $\psi_{q1} = \exp(\alpha_1)$). For reasons of identification, this threshold is considered fixed. Another way to set this identification constraint for ease in the presentation of the empirical results is to absorb this threshold as a constant into the injury risk propensity equation for y_q^* and then set $\psi_1 = 0$ for all q. Both these alternative ways are exactly identical. The first approach is convenient in presenting the motivation of the MGORL model, as in Figures 1 and 2, while the second is convenient for presentation of results. Thus, in Table 5 that presents the model results, there are three main columns. The first column corresponds to the estimates of the moment parameters of β that characterize injury risk propensity (including a constant now). The second column corresponds to ψ_{q2}, and the estimates presented are the moment parameters of θ corresponding to the second threshold demarcating the non-incapacitating and incapacitating injury categories The final column corresponds to ψ_{q3}, and the estimates presented are the moment parameters of θ corresponding to the third threshold demarcating the incapacitating and fatal injury categories.

The effect of each category of variables on the latent injury risk propensity and the two thresholds are discussed in the next sections. We should note here that we extensively tested for unobserved heterogeneity effects on the latent injury risk propensity and the thresholds. But, in our final specification, we did not find any statistically significant unobserved effects. Thus, the mixed generalized ordered response logit (MGORL) model collapsed to a generalized ordered response logit (GORL) model in the final specification. However, we will continue to use the label MGORL for the final model specification. In the model specifications, we also extensively tested for the differential impact of variables between bicycle and pedestrian crashes. But, surprisingly the parameter estimates, for the most part, did not show significant variation between the two non-motorist groups.

5.2.1.1 Non-motorist characteristics

The results regarding the effects of non-motorist characteristics indicate that men and older individuals (> 60 years of age) are prone to high injury risk relative to women and younger individuals (≤60 years of age), respectively. The gender effect is only marginally significant, while the age effect is highly significant. As indicated in earlier studies (see, for example, Stone and Broughton, 2003, Miles-Doan, 1996, and Kim *et al.,* 2007), older individuals tend to have higher perception and reaction times, are more physically fragile, and may suffer from various medical conditions, all of which contribute to their higher injury risk propensity. As expected, non-motorists under the influence of alcohol are likely to have a higher injury risk in accidents, possibly due to generally more reckless behavior and inability to take quick evasive actions. In addition, Andersson and Bunkertorp (2002) indicate that intoxicated non-motorists are more likely to sustain face and head injuries, which are particularly vulnerable body parts for serious injury.

The effects of non-motorist characteristics on the thresholds provide a sense of how the probability of injury in specific injury categories is affected (relative to the case of fixed thresholds; see Figure 2 and corresponding text for a generic discussion of the difference between using fixed thresholds and varying thresholds across crashes). The results indicate that pedestrians are generally more likely to be severely or fatally injured relative to bicyclists (note that the negative sign of the pedestrian variable on the threshold between non-incapacitating and incapacitating injury categories has the effect of increasing the area of the latent injury risk propensity profile under the severely and fatally injured categories). The higher injury severity risk to pedestrians may be a result of pedestrians more likely to be unaware of a crash-developing situation just before the actual impact (and hence may not be able to react in ways to reduce the consequences of the impact). The results also highlight the fact that when an older non-motorist (age > 60) is involved in a crash, the injury severity level is heavily loaded toward the fatal injury category[3].

[3] We also tried a "helmet use" variable for bicyclists under the non-motorist variable category, but this variable turned out to be statistically insignificant. This is, in part, because only about 7% of bicyclists involved in crashes wore helmets.

5.2.1.2 Motorized Vehicle Driver Characteristics

The results associated with the motorized driver characteristics reflect the anticipated higher injury risk propensity to pedestrians and bicyclists struck by alcohol-intoxicated drivers. Further, the effects of the "driver under the influence" variable on the thresholds are thought-provoking. The overall effect of the variable on the probability of each injury severity category depends on the effects on latent propensity and on the two thresholds. Assuming base values for all other variables (note that all variables in the table are dummy variables with a base category), the mean injury risk propensity value is 1.846 (see the parameter on the constant value under the latent propensity column). The threshold values are $\psi_1 = 0$, $\psi_2 = \exp(1.305)$, and $\psi_3 = \exp(1.305) + \exp(1.645)$. The probability values for each injury severity category for this base case are: No injury (0.136), non-incapacitating injury (0.720), incapacitating injury (0.143) and fatal injury (0.001). For individuals exactly similar to the base case, but now who are struck by an alcohol-intoxicated driver, the injury risk propensity is 1.846 + 0.837 = 2.683, $\psi_1 = 0$, $\psi_2 = \exp(1.305 + 0.271)$, and $\psi_3 = \exp(1.305 + 0.271) + \exp(1.645 - 0.25)$. The resulting probability values are: No injury (0.054), non-incapacitating injury (0.824), incapacitating injury (0.119) and fatal injury (0.003). Overall, for crashes corresponding to the base values of the variables, being hit by a driver under the influence of alcohol leads to a decrease in the probability of no injury, an increase in the probability of non-incapacitating injury, a decrease in the probability of incapacitating injury, and an increase in the fatal injury probability. While the actual effects will vary for individuals/crashes not in the base category, the mostly positive impact of the non-base dummy variables on the latent propensity in Table 5 suggest that, in general, the likely result of being struck by an alcohol-intoxicated driver is a non-incapacitating injury or a fatal injury, and not an incapacitating injury This will also become obvious when calculating the elasticity effects. The implication is a bi-modal effect of driver's intoxication level – either the non-motorist is not severely injured or fatally injured. This is a result that needs more scrutiny in further studies.

5.2.1.3 Motorized Vehicle Attributes

The vehicle type involved in the crash with a non-motorist has an influence on the non-motorist's injury risk. Specifically, a non-motorist struck by an SUV has a higher injury risk. The impacts of the vehicle type on the thresholds indicate that crashes involving pick-up trucks increase the likelihood of fatal injuries (because of a reduction in both thresholds). Also, non-motorist crashes with vans increase the likelihood of fatal injuries. Overall, non-motorists involved in vehicular crashes with vehicles other than passenger cars are likely to suffer more serious injuries. The reasons may be attributed to higher speeds, heavier vehicle masses, "above-the-knee" injuries due to higher bumper heights, and larger impact areas on pedestrians and bicyclists (see also Ballesteros *et al.*, 2004 and Lee and Abdel-Aty, 2005).

5.2.1.4 Roadway Characteristics

Two roadway attributes were considered– speed limit on the road the accident occurred, and regulatory signs/control at the accident location. After extensive testing, the speed limit was introduced as a set of dummy variables – “25-50 mph” and “>50 mph”, with the speed limit of “<25 mph” as the base category. The regulatory signs/control at the accident location were introduced in a binary form – whether or not the accident occurred at a signalized intersection.

The results in Table 5 indicate that the latent injury propensity is higher for crashes occurring on roads with higher speed limits and at locations other than signalized intersections. These are intuitive. Speed limits serve as a surrogate measure of actual vehicle speed at the point of impact, while the presence of a signalized intersection reduces vehicle speeds, decreases vehicle-pedestrian and vehicle-bicyclist movement conflicts, and increases drivers’ awareness of pedestrian and bicycle activity (Zazac and Ivan, 2003).

The effects of the speed limit variables on the thresholds indicate the increased likelihood of incapacitating and (particularly) fatal injuries at higher speed limits (over and above what would be predicted by a fixed threshold model). This is particularly so for pedestrians. Stone and Broughton (2003) also point to this sharp rise in fatal injuries at speed limits above 50-60mph. The influence of the “signalized intersection” variable on the final threshold highlights the substantial reduction in fatal injuries at signalized intersections relative to other locations.

5.2.1.5 Environmental Factors

A number of different time-of-day representation schemes were assessed in the MGORL model. The best specification was based on the partitioning of the day into three time periods – day time (6am-6pm), evening (6pm-midnight) and late night (midnight-6am). Earlier attempts to further partition the day time period into the morning peak, evening peak and an off-peak period did not show statistically significant differences in injury severity (this is contrary to Kim *et al.,* 2007, who found an increase in fatal injury during the morning peak). Lighting conditions at the time of the crash were also considered, but turned out not to be statistically significant because of strong correlation effects with the time-of-day variables. The influence of weather conditions simplified to a simple binary representation of presence/absence of snow conditions.

The results in Table 5 underscore the increased latent injury risk propensity in the evening period (6pm-12am) relative to other periods (see Klop and Khattak, 1999, Lee and Abdel-Aty, 2005, and Al-Ghamdy, 2002 for a similar result). In addition, the effects of the evening and late night periods on the thresholds indicate a high likelihood of fatal injuries during these periods. This is likely a consequence of reduced visibility, which, in turn, can lead to slower reaction times and higher impacts at the time of the crash. Further, as suggested by Klop and Khattak (1999), dark conditions may also lead to longer response times by emergency crews. The effect of the “snow” variable on the threshold demarcating the incapacitating and fatal categories shows a lower likelihood of fatal injuries during crashes in snowy conditions. This is perhaps a consequence of low speeds and more careful driving in snow.

5.2.1.6 Crash Characteristics

The direction of impact in a crash affects the injury sustained in the crash. In particular, frontal impacts result in more severe crashes compared to all other kinds of impacts. Frontal impact increases the likelihood of a fatality substantially, as evidenced in the negative effect of this variable on the third threshold. This finding is consistent with Kim *et al.,* 2007, but different from Stone and Broughton (2003) who found a higher fatality rate for back impacts compared to front impacts in their study of cycling crashes in Great Britain. The effect of the "other direction of impact" variable indicates a reduction in the risk propensity, but also a reduction in the third threshold. The net effect is a higher likelihood of fatal injury relative to that predicted by a model with fixed thresholds.

5.2.2 Elasticity Effects

The parameters on the exogenous variables in Table 5 do not directly provide the magnitude of the effects of variables on the probability of each level of non-motorist injury severity. Also, it is not always straightforward to understand the impacts of the coefficients within the MGORL framework. To understand the impact of factors more clearly, we compute the aggregate level "elasticity effects" of variables. This is achieved by first computing the probability of injury severity category k for the non-motorist in crash q. Next, the expected aggregate numbers of non-motorists sustaining an injury of severity level k is computed by summing the individual-level probabilities across all crashes.

With the preliminaries above, one can compute the aggregate-level "elasticity" of any dummy exogenous variable (all exogenous variables in the current model are dummy variables) by changing the value of the variable to one for the subsample of observations for which the variable takes a value of zero and to zero for the subsample of observations for which the variable takes a value of one. We then sum the shifts in expected aggregate shares in the two subsamples after reversing the sign of the shifts in the second subsample, and compute an effective percentage change in expected aggregate shares in the entire sample due to change in the dummy variable from 0 to 1.

The elasticity effects are presented in Table 6 for pedestrians and Table 7 for bicyclists. The effects are provided for both the MGORL model as well as the standard ordered response logit (ORL) model used in earlier pedestrian/bicyclist injury severity studies The numbers in the table may be interpreted as the percentage change in the probability of an injury severity category due to a change in the variable from 0 to 1. For instance, the first number in Table 6 indicates that, according to the ORL model, the probability of a man escaping uninjured in a crash is 13.76% less than the probability of a woman escaping uninjured, other characteristics being equal.

In the rest of this section, we first discuss the elasticity effects from the ORL and MGORL models (section 5.2.2.1), then compare and contrast the effects between pedestrians and bicyclists (section 5.2.2.2), and finally make some general remarks on the strength of the variable effects (section 5.2.2.3).

5.2.2.1 Elasticity effects from the ORL and the MGORL models

The MGORL model is a generalized version of the ORL model, and thus substantial differences in the elasticity effects imply inconsistent estimates from the ORL model. The results in Tables 6 and 7 indeed confirm the severely biased nature of the ORL model elasticity effects. Specifically, while the implied elasticity effects are about the same for the "male", "under the influence of alcohol" for the non-motorist, and "sports utility vehicle" variables, the elasticity effects for all the other variables are drastically different for several injury categories. Just examining the elasticity effects for fatal injury, the MGORL model predicts a much higher fatal injury probability if the non-motorist is elderly (>60 years), the driver of the vehicle is under the influence of alcohol, the vehicle involved in the crash is a pick-up truck (as opposed to other vehicle types), the speed limit on the road of the crash is above or equal to 25 mph, and the crash is a frontal impact. At the same time, a non-motorist involved in a crash at a signalized intersection, and during snow conditions, has a much lower probability of being fatally injured than implied by the ORL model. Further, the ORL model predicts no influence on injury severity due to the non-motorist being hit by a van, while the MGORL model predicts a fatal injury elasticity in the same range as a pick-up. Finally, in the context of the fatal injury category, non-frontal and non-sideways directions of impact (*i.e.*, "other directions of impact" in the tables) have a higher probability of fatal injury relative to sideways impact according to the MGORL model, while such directions of impact have a lower probability of fatal injury relative to sideways impact according to the ORL model. The effects of variables in other injury categories also show differences across the two models, as can be noticed in Tables 6 and 7.

Overall, there are substantial differences in the estimated elasticity effects from the ORL and MGORL models. The MGORL model, because it allows variables to impact both the latent injury propensity and the thresholds, enables a flexible pattern of elasticity effects. This is reflected, for instance, in the effect of the driver (of the vehicle involved in crash) being intoxicated. As is evident from Tables 6 and 7, the MGORL model indicates that crashes involving intoxicated drivers are more likely to lead to non-incapacitating injuries or fatal injuries, but a decrease in incapacitating injuries. This may be a result of some non-motorists becoming alert of the wayward driving of an intoxicated driver and taking quick evasive action to reduce impact severity, resulting in a decreased likelihood of incapacitating injuries. However, several non-motorists may not become aware, and so are fatally injured. This kind of trend reversal of the effect of variables on the successive injury severity categories cannot be reflected by the ORL model, which constrains the elasticity effects to have a more rigid (and monotonic) trend in elasticity effects from the lowest category of injury severity to the highest (see Bhat and Pulugurta (1994) for a detailed theoretical discussion of this property of the ORL model).

5.2.2.2 Elasticity effect comparison between pedestrians and bicyclists

In this section, we confine our attention to the estimates from the MGORL model. An important finding from Tables 6 and 7 is that the general pattern and magnitude of elasticity effects of variables on injury severity is similar across pedestrians and bicyclists. This is an encouraging result from the standpoint of designing strategies to alleviate non-motorist injury severity levels in crashes, since a single uniform set of strategies may be identified and implemented. Nonetheless, there are some important differences in the elasticity effects for pedestrians and bicyclists. In particular, bicyclists over the age of 60 years, under the influence of alcohol, and hit by pick-up trucks/vans are more likely to be incapacitatingly or fatally injured in crashes than pedestrians over 60 years, under the influence of alcohol, and hit by a pick-up truck/van, respectively. Crashes on roadways with a speed limit of 25-50 mph are likely to lead to more incapacitating or fatal injuries in pedestrians than bicyclists, while the reverse is true for crashes on roadways with a speed limit of over 50 mph. The environmental and crash factor elasticity effects show the higher injury severity levels for bicyclists compared to pedestrians for crashes occurring during the evening/night periods and for frontal impacts. In general, with some exceptions, the effect of the variables in Tables 6 and 7 is to increase the probability of incapacitating and fatal injuries for bicyclists relative to pedestrians.

5.2.2.3 Strength of variable effects and implications

Tables 6 and 7 suggest that the most important variables affecting injury severity level sustained by non-motorists are: (1) whether or not the non-motorist is over 60 years of age, (2) speed limit on roadway, (3) location of crash (crashes at signalized intersection lead to reduced injury severity compared to crashes at other roadway locations) and (4) time-of-day of crash (dark periods of the day lead to higher injury severity). The intoxication level of non-motorist and drivers, vehicle type involved in the crash, and crash characteristics also have important effects, but not as much as the factors identified earlier.

The variable effects have important implications for education and training, traffic regulation and control, as well as planning and design of pedestrian/bicycle facilities. In terms of *education and training*, the results reinforce the need to educate both non-motorists and vehicle drivers about the risks of driving under the influence (DUI) of alcohol. Unfortunately, darkness also plays an important role in injury severity and, therefore, the combination of DUI and driving late night after parties (especially, between 12 am-6 am) is particularly deadly (and much more so than predicted by the ORL model used in earlier studies). This issue needs to be emphasized in the education and training of motorized vehicle drivers, and not just the individual and separate effects of alcohol use and the dangers of driving at night time. Similarly, non-motorists should also be made aware of the risks of alcohol use and night time travel, particularly the combination of the two. Further, older adults are particularly prone to fatal injuries due to greater fragility (the ORL model used in earlier studies underestimates this effect), and thus recommendations to decrease injury risk due to other factors are warranted (for example, older drivers may be advised, in particular, to avoid walking/bicycling during the night time in places with medium-to-heavy vehicular traffic). Encouraging non-motorists to wear “reflector” gear to improve visibility is another element of education and training countermeasures.

Traffic regulation and control countermeasures can include precluding non-motorists and motorists from sharing the same pavement on high speed roads and/or on roads with a significant fraction of heavy vehicles. Signs need to be posted to communicate this to non-motorists. In areas with heavy pedestrian and bicycle traffic, such as in residential areas, the results suggest the need to restrict the speed limit to 25 mph. Good street lighting and illumination, and additional traffic signal installation, also can constitute effective countermeasures in areas with heavy non-motorist traffic.

Finally, the results also inform the *planning and design of pedestrian/bicyclist facilities*. On high speed limit roads (particularly those over 50 mph), bicycle facilities should be designed to be an off-roadway bicycle lane (a bikeway physically separated from motorized vehicle traffic by an open space or barrier) or at least a clearly demarcated bicycle lane (a designated portion of the roadway striped for bicycle use). Also, in selecting bicycle highways, decision-makers should review adjoining roadway speed limits, vehicle mix of traffic, and the presence of good illumination. Interestingly, our results also suggest that there may be value to selecting bicycle paths along roadway corridors with several signalized intersections, even if this may not be desirable from a bicyclist travel standpoint.

5.2.3 Measures of Fit

It is clear from Section 5.2.2.1 that the substantive implications for policy analysis from the ORL and MGORL model are quite different in the current empirical context. These differences suggest the need to apply formal statistical tests to determine the structure that is most consistent with the data.

Given that the MGORL model is a generalized version of the ORL model, the two models can be compared using a likelihood ratio test in the estimation sample. The log-likelihood value at convergence of the final MGORL model is -2667.6, while the corresponding value for the ORL model is -2732.9 (the log-likelihood value of the market share model is -2867.9). The likelihood ratio test value for comparing the MGORL model with the ORL model is 130.6, which is larger than the critical chi-square value with 18 degrees of freedom at any reasonable level of significance (note that the ORL model restricts all the non-constant parameters in the threshold columns of Table 5 to 0; there are 18 such parameters).

We also evaluated the performance of the ORL and MGORL models on various market segments of the estimation sample (Ben-Akiva and Lerman, 1985 refer to such predictive tests as market segment prediction tests). We use both aggregate and disaggregate measures of fit. At the aggregate level, we compare the predicted and actual (observed) shares of injuries in each severity level and compute the root mean square error (RMSE) and the mean absolute percentage error. At the disaggregate level, we compute the predictive log-likelihood and compare the two models using a chi-squared test. The results are provided in Table 8. The predicted shares from the MGORL model are clearly much closer to the true shares by both aggregate measures of fit. The predictive performance from the MGORL model is also superior to that of the ORL model based on the predictive log-likelihood value. The differences are statistically significant when compared to the chi-squared critical value of 28.87 (at the 0.05 level of significance) for each market segment. Overall, all the fit statistics indicate the superior performance of the MGORL model over the ORL model from a data fit standpoint.

6. Conclusions

This paper proposes an econometric structure for injury severity analysis that recognizes the ordinal nature of the categories in which injury severity are recorded, while also allowing flexibility in capturing the effects of explanatory variables on each ordinal category and allowing heterogeneity in the effects of contributing factors due to the moderating influence of unobserved factors. The model developed here, referred to as the mixed generalized ordered-response logit (MGORL) model, generalizes the standard ordered-response models used in the extant literature for injury severity analysis. The MGORL model is very flexible, and allows trend reversals in the elasticity effect of variables on the probabilities of successive injury severity categories. On the other hand, the standard ordered-response model constrains the elasticity effects to be more rigid and monotonic from the lowest category of injury severity to the highest. The MGORL formulation developed here also immediately satisfies the required ordering conditions of the thresholds for each crash. To our knowledge, this is the first such formulation to be proposed and applied in the econometric literature in general, and in the safety analysis literature in particular. The MGORL model is estimated using a maximum simulated likelihood method using quasi-Monte Carlo draws.

The MGORL model is applied to examine non-motorist injury severity in accidents, using the 2004 General Estimates System (GES) database. The study considers a comprehensive set of potential determinants of non-motorized injury severity, including non-motorist and motorized vehicle driver characteristics, motorized vehicle attributes, roadway characteristics, environmental factors and crash characteristics. The study appears to be the first to compare and contrast the effects of variables on injury severity between pedestrians and motorists.

There are several important empirical findings. First, the ORL model used in extant studies produces inconsistent estimates of the effects of several variables in the current empirical context. For instance, the ORL model substantially underestimates the fatal injury probability for the elderly (> 60 years), non-motorists hit by an alcohol-intoxicated driver and/or a driver with a pick-up truck, and crashes occurring on roads with a speed limit over 25 mph. The incorrect evaluation of the effects of determining factors can lead to misinformed policy actions. Second, an important result is that the general pattern and relative magnitude of elasticity effects of injury severity determinants are similar for pedestrians and bicyclists. This is an encouraging result from the standpoint of designing countermeasures. To the extent that earlier research on non-motorized injury severity has focused solely on pedestrians or on bicyclists, they have been unable to make such an important conclusion. Third, even though the pattern and relative magnitude of elasticity effects are the same across pedestrians and bicyclists, the absolute magnitudes indicate that bicyclists over 60 years, under the influence of alcohol, hit by pick-up trucks, and involved in accidents on high speed roads (> 50 mph) are likely to be more severely injured than pedestrians over 60 years, under the influence of alcohol, hit by pick-up trucks, and involved in accidents on high speed roads, respectively. However, pedestrians are the ones more likely to be severely injured relative to bicyclists for crashes on roads with a speed limit between 25-50 mph. Fourth, the most important variables influencing non-motorist injury severity are the age of the individual (the elderly are more injury-prone), the speed limit on the roadway (higher speed limits lead to higher injury severity levels), location of crashes (those at signalized intersections are less severe than those elsewhere), and time-of-day (darker periods lead to higher injury severity). Fifth, the results have important implications for education and training, traffic regulation and control, and planning of pedestrian/bicycle facilities, as discussed in Section 4.3.2.3. Sixth, the MGORL model clearly provides a much better data fit than the ORL model on the estimation sample as well as for specific segments, reinforcing the inconsistent results that are obtained from the ORL model. Overall, the current research contributes to the literature from both methodological and empirical standpoints.

The paper, however, is not without its limitations. As with several earlier studies, the use of police-reported crashes can skew injury severity levels toward more severe crashes (since crashes with no injury or minor injury may not be reported and so may be under-represented in the accident database). Further, the scope of the current research is limited to non-motorized injury severity in crashes with a single motorized vehicle. While these are the most common type of crashes, the analysis can be extended to other types of crashes. Also, there is room for improving the model specification by including additional variables, such as grades, road curvature, detailed roadway geometrics, and average speeds at the location of crash (rather than speed limits). The specification adopted in the current paper, while quite comprehensive, is limited by the variables available in the GES data. Finally, it should also be pointed out that, while age of the motorized vehicle driver did not turn out to be a statistically significant determinant of non-motorized individual injury severity in the current study, this may be attributed to the lack of adequate crashes involving old drivers (specifically, those over the age of 70 years) in the sample. As the age of motorist drivers increases in the US and other developed countries, it is important that a comprehensive evaluation of accidents involving older drivers be undertaken. This, along with the travel pattern needs of the elderly (see Golob and Hensher, 2007 and Hensher, 2007), may help inform the design of policies that balance travel needs of this growing population group with any road safety-related concerns associated with their driving.

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Table 1: Descriptive Analysis Studies of Non-Motorist Injury Severity

Study	Non-motorized User Type		Injury Severity Representation	Data Source	Analysis framewor employed	Categories c independent Variabl considered	Summary Findings
	Pedestri an	Bicyclist					
Atkins *et al.*, (198	Yes	No	Abbreviated injury score (AIS) – 5 category ordinal variable	Road traffic accidents in Oxford, (1983-1984)	Frequency Analysis	Non-motorist characteristics	• The study observed a peak in injuries to pedestrians aged 16-65 years 11 pm and 12 am • Pedestrian alcohol use did not influence injury severity.
						Motorized Vehicle attributes	• An increase in injury severity with an increase in vehicle weight are observed
Jehle and Cottington (1988)	Yes	No	Injury severity score – continuous variable (ISS)	Pedestrian accident victims Pittsburgh, PA (1982-1983)	Chi-squared test	Non-motorist characteristics	• The study concludes that pedestrians intoxicated are subject to higher ISS • The proportion of alcohol related accidents were higher in the 25-34 age group.
Holubowycz (199	Yes	No	Fatal vs. serious injury – binary variable	Office of road safety of department of road transport and police traffic intelligence center and royal Adelaide hospital (1981-1992)	Chi-squared test and student's *t*-test	Non-motorist characteristics	• The highest fatality rates were seen in elders aged 75 or more. • A large proportion of the pedestrian injured seriously or fatally were males • Among the fatally injured young and middle-aged males alcohol consumption was high
Jensen (1999)	Yes	No	4 category ordinal variable	Denmark police reported cases for 47 Danish cities (1995)	Frequency analysis	Roadway characteristics	• Increased speed limit leads to higher proportion of fatalities in traffic crashes.
Al-Ghamdi (2002)	Yes	No	1) Fatal vs nonfatal – binary variable 2) Three category ordinal variable	Pedestrian vehicle crashes in Riyadh (1997-1999)	Chi-squared test and odds ratio	Motorized Vehicle attributes	• The relationship between injury severity and vehicle type was statistically insignificant
						Roadway characteristics	• The odds of sustaining a severe injury are higher for crashes occurring on two-way roadways with a median.
						Environmental factors	• The odds of being killed at night are 1.81 times higher than for being killed during the day
Stone and Broughton (2003)	No	Yes	Fatal vs. nonfatal – binary variable	Police reported crashes in England, Wales and Scotland (1990-1999)	Frequency analysis	Non-motorist characteristics	• A higher incidence of fatalities were observed in adults older than 50 years. • Fatality rates were not significantly different for males and females
						Roadway characteristics	• Fatality rates increase markedly with increase in speed limits
						Environmental factors	• The study studied the influence of lighting on fatalities and found that darkness with street lighting has the lowest fatality rate. • Higher percentage of fatalities occur between 9 pm - 6 am.
						Crash characteristics	• The fatality rates for back impacts are higher than the corresponding numbers for frontal impacts • A significant number of serious (resulting in serious injury/fatality) bicycle accidents (94%) occur without a collision with another vehicle
Lefler and Gabler (2004)	Yes	No	Abbreviated injury scale – 6 category ordinal variable(AIS)	Pedestrian Crash Data Study (PCDS) (1994-1998)	Frequency and Cross-tabulation analysis	Motorized Vehicle attributes	• The likelihood of pedestrians sustaining a fatal injury is higher in collisions with light truck vans
						Roadway characteristics	• Higher speed limits are associated with severe injuries on the AIS scale.

Table 2: Modeling Studies of Non-Motorist Injury Severity

<table>
<tr><th rowspan="2">Study</th><th colspan="2">Non-motorist User Type</th><th rowspan="2">Injury severity representation</th><th rowspan="2">Data Source</th><th rowspan="2">Analysis framework employed</th><th rowspan="2">Categories of independent Variables considered</th><th rowspan="2">Summary Findings</th></tr>
<tr><th>Pedestrian</th><th>Bicyclist</th></tr>
<tr><td rowspan="6">Pitt et al., (1990)</td><td rowspan="6">Yes</td><td rowspan="6">No</td><td rowspan="6">1) Injury severity score- continuous score (ISS)
2) Serious Vs Non serious injury – binary variable</td><td rowspan="6">Pedestrian injury causation study from National highway traffic safety administration</td><td rowspan="6">Analysis of Variance for ISS
Logistic regression for serious vs. non-serious injury</td><td>Non-motorist characteristics</td><td>• Children aged less than five years sustained more severe injuries and children older than 9 years sustained less severe injuries compared to the 5 – 9 age group
• Gender based differences in injury severity were insignificant</td></tr>
<tr><td>Motorized Vehicle Driver characteristics</td><td>• Driver sex, gender and alcohol use were statistically insignificant</td></tr>
<tr><td>Motorized Vehicle attributes</td><td>• Vehicle speed > 30 mph resulted in increasing the likelihood of a severe injury
• Vehicle characteristics (such as bumper height, hood height and lead angle) did not influence injury severity</td></tr>
<tr><td>Roadway characteristics</td><td>• Roadway classification, travel lane, and presence of traffic control also did not influence injury severity
• Injury severity was highest in residential zones
• The study suggests use of automated traffic devices to enhance safety</td></tr>
<tr><td>Environmental factors</td><td>• The most severe injuries occurred between 6 am – 9 am and the least severe injuries occurred between 12 pm- 3 pm</td></tr>
<tr><td>Crash characteristics</td><td>• Manner of impact did not affect injury severity.
• Pedestrians moving within the road were more severely injured</td></tr>
<tr><td rowspan="4">Miles-Doan (1996)</td><td rowspan="4">Yes</td><td rowspan="4">No</td><td rowspan="4">1) Fatal vs. nonfatal –binary variable
2) Serious/fatal vs. minor/no injury- binary variable
3)Fatal vs. seriously injured</td><td rowspan="4">Florida department of highway safety (1988-1990)</td><td rowspan="4">Logistic regression</td><td>Non-motorist characteristics</td><td>• An increase in age led to an increase in the severity odds
• Pedestrian alcohol consumption increased the odds of serious injury or a fatality</td></tr>
<tr><td>Roadway characteristics</td><td>• Speed limits > 40mph affects injury severity significantly
• Accidents occurring in rural locations are found to result in more severe injuries</td></tr>
<tr><td>Environmental factors</td><td>• The injuries occurring during the “dark “ periods of the day were more severe</td></tr>
<tr><td>Crash characteristics</td><td>• Crashes where a vehicle collides straight ahead with the pedestrian result in severe injuries</td></tr>
<tr><td rowspan="2">Klop and Khattak (1999)</td><td rowspan="2">No</td><td rowspan="2">Yes</td><td rowspan="2">5 category ordinal variable</td><td rowspan="2">North Carolina Highway Safety Information System (1990-1993)</td><td rowspan="2">Ordered response model</td><td>Roadway characteristics</td><td>• Grades (both straight and curved) result in increasing the injury severity of bicyclist
• Higher average traffic results in less severe injuries
• Influence of speed limit on injury propensity was insignificant
• The crash location and presence of shoulder on the roadway did not affect injury severity</td></tr>
<tr><td>Environmental factors</td><td>• Crashes occurring in dark lighting result in severe injuries.
• Presence of fog on roadways increases the likelihood of severe injury</td></tr>
</table>

Study	Non-motorist User Type: Pedestrian	Non-motorist User Type: Bicyclist	Injury severity representation	Data Source	Analysis framework employed	Categories of independent Variables considered	Summary Findings
Ballesteros *et al.*, (2003)	Yes	No	1) Fatal vs. nonfatal – binary variable 2) Injury severity score (ISS) ≥ 16 vs. ISS < 16 –binary variable	Maryland Automated Accident Reporting System (1995-1999)	Logistic regression analysis	Motorized Vehicle attributes	• Pedestrians hit by SUVs and pick-ups were more likely to suffer fatal injuries compared to conventional passenger cars and vans. • Controlling for vehicle weight and speed limit increased the odds of a injury when a van is involved.
						Roadway characteristic	• With increasing speed limits, pedestrian mortality and ISS values increased.
Zajac and Ivan (2003)	Yes	No	5 category ordinal variable	Connecticut department of transportation (1989-1998)	Ordered response model	Non-motorist characteristics	• Pedestrians older than 65 years are prone to severe injuries • Pedestrian and driver alcohol consumption resulted in severe injuries
						Motorized Vehicle Driver characteristics	• Motorized vehicle driver alcohol intoxication results in increased pedestrian injury severity
						Roadway characteristic	• Increase in roadway width increased injury severity propensity • Crashes occurring in downtown and compact residential areas were found to result in lower injury severity compared to the crashes in low-density residential areas. Also, crashes occurring in low and medium density commercial areas result in less severe injuries compared to the crashes occurring in village and downtown fringe areas
						Environmental factors	• Lighting and weather were statistically insignificant in the analysis
Roudsari *et al.*, (2004)	Yes	No	1) Injury severity score (ISS) ≥ 15 vs. ISS <15 – binary variable 2) ISS ≥ 9 vs. ISS <9 – binary variable 3) Abbreviated injury scale (AIS) ≥4 vs. AIS < 4 – binary variable	Pedestrian accidents from Buffalo, Chicago, Dallas, Fort Lauderdale, San Antonio, and Seattle (1994-1998)	Logistic regression analysis	Non-motorist characteristics	• Adult mortality is higher than children mortality in crashes.
						Motorized Vehicle attributes	• After controlling for pedestrian age and speed at impact, light truck vans are associated with higher odds of severe injuries • Higher speeds resulted in severe injuries
Lee and Abdel-Aty (2005)	Yes	No	5 category ordinal variable	Florida traffic crash records database (1999-2002)	Ordered response model	Non-motorist characteristics	• Pedestrians older than 65 are prone to severe injuries • Females are slightly more likely to be severely injured • Pedestrian alcohol use increases severity propensity
						Motorized Vehicle attributes	• Non-sedan (van, truck and bus) crashes result in more severe injuries • Increase in speed also increase the injury severity sustained
						Roadway characteristic	• Rural areas are more likely to result in severe crashes • If the crash occurs at a crossing with a a traffic control device the propensity to be injured is lower.

Study	Non-motorist User Type: Pedestrian	Non-motorist User Type: Bicyclist	Injury severity representation	Data Source	Analysis framework employed	Categories of independent Variables considered	Summary Findings
						Environmental factors	• Dark lighting and adverse weather increase the injury severity propensity
Kim *et al.*, (2007)	No	Yes	4 category ordinal variable	North Carolina accident data (1997-2002)	Multinomial logit model	Non-motorist characteristics	• Bicyclists older than 55 are more susceptible to fatalities • Bicyclist alcohol consumption increases likelihood of fatal and incapacitating injuries
						Motorized Vehicle Driver characteristics	• Motorized vehicle driver alcohol intoxication results in increased propensity of incapacitating and fatal injuries
						Motorized Vehicle attributes	• Heavy trucks and pickups increase the likelihood of fatal and incapacitating injuries. • Increase in speed increases the likelihood of non-incapacitating, incapacitating and fatal injuries
						Roadway characteristics	• Crashes occurring on curved roads result in more fatalities
						Environmental factors	• Inclement weather and darkness increases the likelihood of fatalities • Crashes occurring during the AM peak (6 am – 10 am) and weekends increase the likelihood of fatality
						Crash characteristics	• Frontal impacts increase the odds of a fatality
Sze and Wong (2007)	Yes	No	Fatal vs. serious injury – binary variable	Traffic crashes collected by the Hong Kong transportation department (1991-2004)	Logistic regression	Non-motorist characteristics	• Males aged less than 15 years were subject to lower risk of a fatality. Pedestrians older than 65 are more likely to suffer death
						Roadway characteristics	• Crashes occurring on roadways with speed limit > 50 km/h increased the likelihood of fatalities • Crashes occurring on intersections with traffic signals are severe than intersections with other traffic signs. • Multi –dual carriageway roads are more riskier compared to one-way roadways
						Environmental factors	• The odds of a fatality are higher for crashes occurring between 7 pm – 7 am
						Crash characteristics	• Pedestrian crossing the roads are subject to more severe injuries • Pedestrian being inattentive increases the odds of sustaining a fatality

Table 3: Distribution of non-motorist injury severity by non-motorist type

Injury severity category	Pedestrian	Bicyclist	All Non-motorists
No (and possible?)injury	135 (7.8%)†	89 (7.3%)	224 (7.6%)
Non-incapacitating injury	951 (55.3%)	863 (70.6%)	1814 (61.6%)
Incapacitating injury	541 (31.4%)	250 (20.4%)	791 (26.9%)
Fatal injury	94 (5.5%)	21 (1.7%)	115 (3.9%)
Total	1223 (100.0%)	1721 (100.0%)	2944 (100.0%)

†The percentage values sum to 100 across rows for each column.

Table 4: Distribution of non-motorist injury severity by non-motorist alcohol intoxication

Injury severity category	Non-motorist was alcohol intoxicated?		All Non-motorists
	No	Yes	
No (and possible?)injury	217 (8.0%)†	7 (2.8%)	224 (7.6%)
Non-incapacitating injury	1688 (62.6%)	126 (51.2%)	1814 (61.6%)
Incapacitating injury	699 (25.9%)	92 (37.4%)	791 (26.9%)
Fatal injury	94 (3.5%)	21 (8.5%)	115 (3.9%)
Total	2698 (100.0%)	246 (100.0%)	2944 (100.0%)

†The percentage values sum to 100 across rows for each column.

Table 5: Mixed Generalized Ordered Response Logit results

Variables	Latent Propensity	Threshold between Non-incapacitating and Incapacitating injury	Threshold between Incapacitating and Fatal injury
Latent Propensity component			
Constant	1.846 (12.94)	1.305 (36.26)	1.645 (11.49)
Non-motorist Characteristics			
Pedestrian (Bicyclist is the base)	---	-0.103 (-2.67)	---
Male	0.159 (1.85)	---	---
Age Variables (age ≤ 60 years is base)			
> 60 years	0.667 (5.26)	---	-0.536 (-4.61)
Under the influence of alcohol	0.455 (3.47)	---	---
Motorized Vehicle Driver Characteristics			
Under the influence of alcohol	0.837 (2.14)	0.271 (2.87)	-0.250 (-1.53)
Motorized Vehicle Attributes			
Sports utility vehicle	0.364 (3.15)	---	---
Pick-up truck	---	-0.070 (-2.18)	-0.197 (-1.98)
Van	---	---	-0.237 (-1.70)
Roadway Design Characteristics			
Speed Limit			
25-50mph	0.218 (1.97)	---	-0.225 (-2.01)
>50 mph	0.605 (3.06)	---	-0.679 (-3.93)
Speed limit > 25mph * pedestrian	---	-0.117 (-2.61)	---
Accident Location (stop signs, warning signs, regulatory signs, and no signs are base)			
Signalized Intersection	-0.300 (-3.32)	---	0.387 (3.43)
Environmental Factors			
6pm - 12am	0.297 (3.43)	---	-0.352 (-3.82)
12am - 6am	---	-0.304 (-4.66)	-0.365 (-2.59)
Snow	---	---	0.538 (1.60)
Crash Characteristics			
Direction of Impact (sideways impact is the base)			
Frontal Impact	0.447 (3.20)	0.072 (1.64)	-0.226 (-2.38)
Other directions of impact	-0.734 (-2.91)	---	-0.603 (-2.23)
Log-likelihood at convergence	-2667.6		
Number of observations	2944		

Table 6: Elasticity Effects for Pedestrians

Variables	ORL				MGORL			
	No injury	**Non-incapacitating injury**	**Incapacitating injury**	**Fatal Injury**	**No injury**	**Non-incapacitating injury**	**Incapacitating injury**	**Fatal Injury**
Non-motorist Characteristics								
Male	-13.76	-4.02	7.92	13.44	-14.61	-4.25	8.69	13.05
Age Variables								
> 60 years	-58.28	-26.03	43.49	99.38	-49.28	-20.64	9.18	231.82
Under the influence of alcohol	-37.79	-14.93	26.48	52.56	-35.46	-13.78	25.34	42.57
Motorized Vehicle Driver Characteristics								
Under the influence of alcohol	-2.68	-0.81	1.58	2.75	-56.59	12.61	-15.39	39.79
Motorized Vehicle Attributes								
Sports utility vehicle	-26.79	-9.50	17.39	33.35	-29.36	-10.69	19.99	33.69
Pick-up truck	-10.16	-3.16	6.08	10.80	0	-8.70	5.18	60.44
Van	---	---	---	---	0	0	-7.84	47.24
Roadway Design Characteristics								
Speed Limit								
25-50mph	-40.19	-11.11	22.29	37.41	-20.13	-20.14	26.61	80.37
>50 mph	-65.94	-34.64	53.79	144.11	-44.20	-33.73	6.93	376.10
Accident Location								
Signalized Intersection	33.86	8.95	-18.33	-29.60	28.76	7.68	-7.02	-79.21
Environmental Factors								
6pm – 12am	-30.37	-9.89	51.89	131.31	-25.70	-8.30	4.52	96.52
12am – 6am	-63.57	-32.76	18.73	33.73	0	-35.51	26.23	216.14
Snow	14.84	3.94	-8.03	-13.18	0	0	11.74	-70.74
Crash Characteristics								
Direction of Impact (sideways impact is base)								
Frontal Impact	-27.06	-7.57	15.18	25.16	-42.60	-2.82	5.74	55.33
Other direction of impact	97.88	15.72	-39.33	-53.48	87.04	14.23	-50.49	31.36

Table 7: Elasticity Effects for Bicyclists

Variables	ORL				MGORL			
	No injury	Non-incapacitating injury	Incapacitating injury	Fatal Injury	No injury	Non-incapacitating injury	Incapacitating injury	Fatal Injury
Non-motorist Characteristics								
Male	-13.51	-1.82	10.07	13.61	-15.01	-1.98	11.50	14.19
Age Variables								
> 60 years	-54.57	-17.18	63.95	110.78	-47.59	-12.86	33.52	350.79
Under the influence of alcohol	-36.23	-8.84	36.57	57.50	-34.93	-8.02	37.06	50.75
Motorized Vehicle Driver Characteristics								
Under the influence of alcohol	-2.57	-0.40	2.05	2.87	-55.85	13.65	-27.46	25.26
Motorized Vehicle Attributes								
Sports utility vehicle	-26.08	-5.16	23.45	34.74	-29.57	-5.88	28.62	38.48
Pick-up truck	-9.72	-1.61	7.99	11.31	0	-6.54	15.51	84.11
Van	---	---	---	---	0	0	-5.25	62.63
Roadway Design Characteristics								
Speed Limit								
25-50mph	-38.23	-5.18	28.56	38.99	-20.08	-2.83	11.94	67.57
>50 mph	-63.86	-23.96	82.73	161.52	-43.73	11.48	19.96	437.65
Accident Location								
Signalized Intersection	32.43	3.91	-23.05	-30.58	28.84	3.57	-16.05	-89.60
Environmental Factors								
6pm – 12am	-28.69	-9.89	78.23	150.42	-25.29	-4.45	14.32	130.23
12am – 6am	-60.81	-22.50	24.95	36.16	0	-29.68	70.10	385.68
Snow	14.17	1.75	-10.18	-13.62	0	0	6.54	-77.92
Crash Characteristics								
Direction of Impact (sideways impact is base)								
Frontal Impact	-25.46	-3.65	19.54	26.73	-41.33	0.61	8.60	64.66
Other direction of impact	92.50	3.20	-45.49	-53.91	88.60	4.15	-53.33	52.76

Table 8: Aggregate Measures of Fit in Estimation Sample

Injury Categories/Measures of fit	Pedestrians			Bicyclists			Older Non-motorists			Frontal impacts		
	Actual shares	ORL predictions	MGORL predictions	Actual shares	ORL predictions	MGORL predictions	Actual shares	ORL predictions	MGORL predictions	Actual shares	ORL predictions	MGORL predictions
No (and possible?)injury	7.84	6.04	7.44	7.28	9.89	7.93	3.91	3.91	4.98	6.51	6.62	6.29
Non-incapacitating injury	55.26	57.70	55.55	70.56	65.90	70.07	53.02	49.82	51.25	60.50	59.58	60.88
Incapacitating injury	31.44	31.38	31.73	20.44	21.59	20.28	30.96	39.15	32.38	28.21	29.41	28.32
Fatal injury	5.46	4.94	5.29	1.72	2.62	1.72	12.10	7.12	11.39	4.77	4.40	4.50
Number of observations	1721	1721	1721	1223	1223	1223	281	281	281	1843	1843	1843
Root mean square error (RMSE)	---	1.54	0.30	---	2.77	0.42	---	5.05	1.31	---	0.78	0.26
Mean absolute percentage error (MAPE)	---	9.28	2.46	---	25.14	2.62	---	18.41	10.28	---	3.84	2.51
Predictive likelihood ratio test	96.1 > $\chi^2_{18,0.05} = 28.87$			42.1 > $\chi^2_{18,0.05} = 28.87$			33.5 > $\chi^2_{18,0.05} = 28.87$			88.3 > $\chi^2_{18,0.05} = 28.87$		

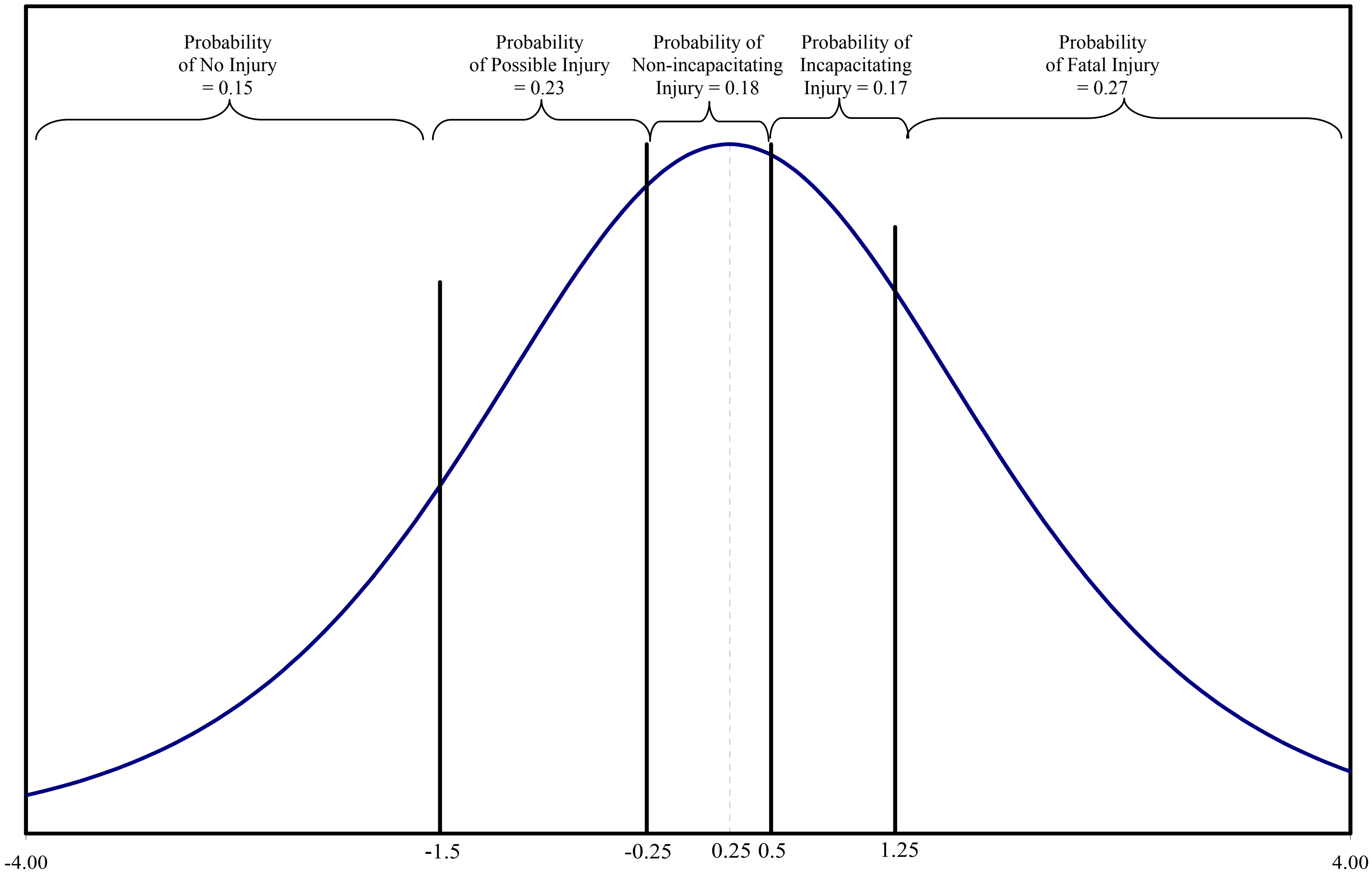

Figure 1: Probability values for injury severity with fixed thresholds for the two crash groups of (a) intoxicated motorists who hit bicyclists and (b) non-intoxicated motorists who hit bicyclists head-on

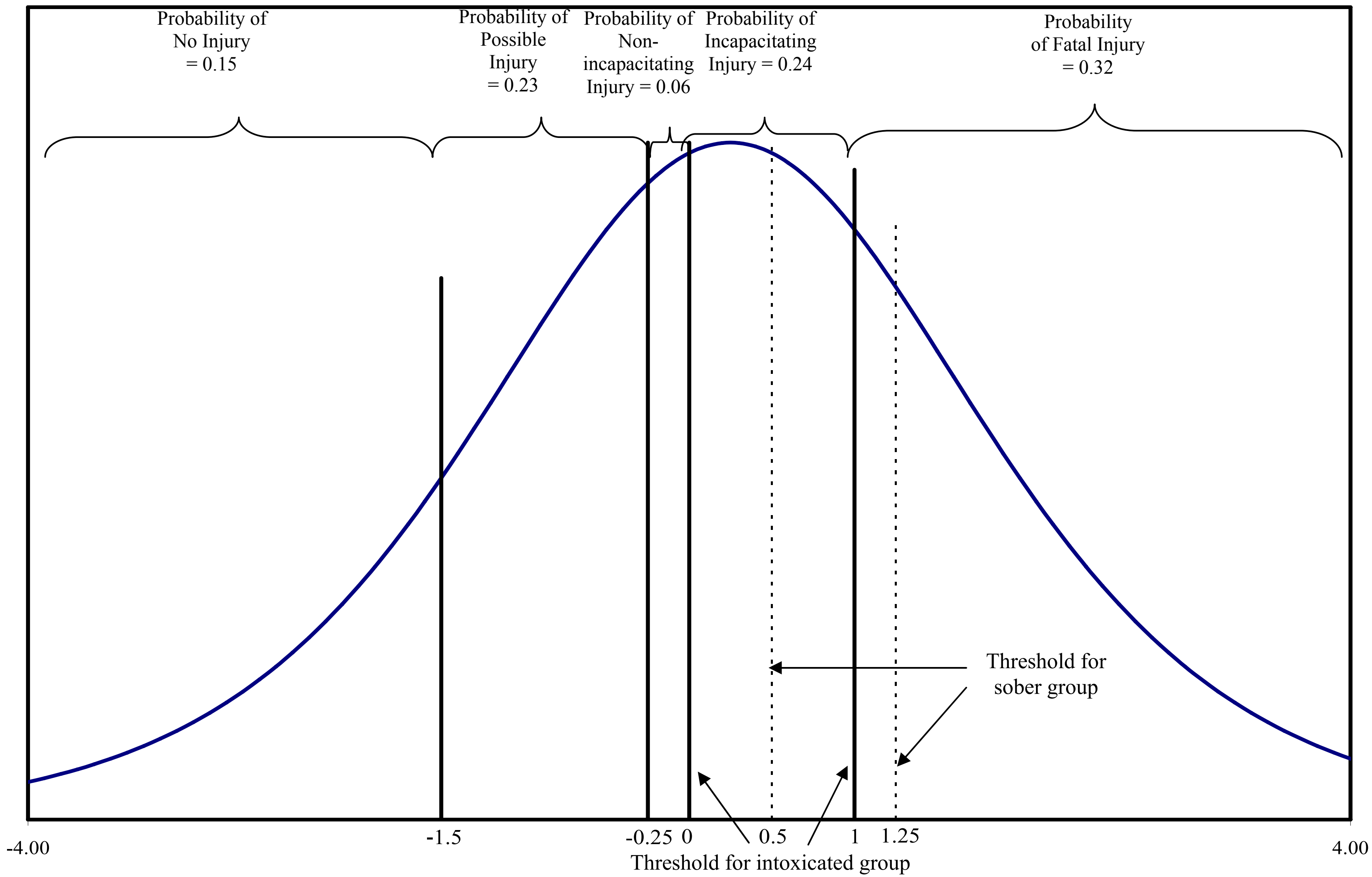

Figure 2: Probability values for injury severity with varying thresholds across individuals: Thresholds for intoxicated motorists who hit bicyclists sideways.