Research in Transportation Economics 43 (2013) 123–136

Contents lists available at SciVerse ScienceDirect

Research in Transportation Economics

journal homepage: www.elsevier.com/locate/retrec

Examining pedestrian-injury severity using alternative disaggregate models

Kibrom A. Abay*

University of Copenhagen, Department of Economics, Øster Farimagsgade 5, Building 26, DK-1353 Copenhagen K, Denmark

ARTICLE INFO

Article history:
Available online 3 January 2013

JEL classification:
R41

Keywords:
Pedestrian-injury severity
Ordered and unordered response models
Crime history

ABSTRACT

This paper investigates the injury severity of pedestrians considering detailed road user characteristics and alternative model specification using a high-quality Danish road accident data. Such detailed and alternative modeling approach helps to assess the sensitivity of empirical inferences to the choice of these models.

The empirical analysis revealed that detailed road user characteristics such as crime history of drivers and momentary activities of road users at the time of the accident provide an interesting insight in injury severity analysis. Likewise, the alternative analytical specification of the models reveals that some of the conventionally employed fixed-parameters injury severity models could underestimate the effect of some important behavioral attributes of the accidents. For instance, the standard ordered logit model underestimated the marginal effects of some of the variables considered, and forced some important variable effects to be statistically insignificant, while they remain significant predictors in the other relatively flexible models.

1. Introduction

Walking is an integral part of human activity which provides important economic and health benefits. It is environmentally friendly, accessible, cost-effective, and accrues significant health benefits. For instance, according to NZTA (2010) the total health benefit of walking was estimated to be $2.6 per each kilometer walked (see also, Rahul & Verma, 2012). However, pedestrians are markedly vulnerable to traffic injury. According to WHO (2009a), vulnerable road users (including pedestrians, cyclists and drivers of motorized two-wheelers) account for 46% of global traffic deaths. Similarly, in Denmark, pedestrians' death account for 18% of all road fatalities in the year 2009 (ITF, 2011).[1] Thus, though walking offers immense strategic benefits, it involves a significant trade-off as pedestrians bear the highest burden of traffic injury. Hence, policy makers that advocate pedestrianization or economists who are keen at investigating the economic appraisal of non-motorized mobility need to explore the ultimate causes of the vulnerability of pedestrians to traffic injury. Likewise, safety planners and public officials involved in cost–benefit analysis of road investment projects crucially need accurate estimate on the effect of the multifaceted attributes of road accidents. Intuitively, all these require exploring the leading causes of road accidents, which involves two-step approaches aimed at exploring the ultimate causes of traffic accidents, and investigating the injury severity sustained by road users. Generally, such an investigation also helps public safety officials design economically efficient safety measures and mobility management strategies that reduce the frequency and severity of traffic accidents.

As part of the efforts to explore the leading causes for the vulnerability of pedestrians to traffic injury, previous studies have investigated the effects of different attributes of road accidents on the injury severity level sustained by pedestrians (see Ballesteros, Dischinger, & Langenberg, 2004; Eluru, Bhat, & Hensher, 2008; Kim, Ulfarsson, Shankar, & Kim, 2008; Kim, Ulfarsson, Shankar, & Mannering, 2010; Lee & Abdel-Aty, 2005; Sze & Wong, 2007; Zajac & Ivan, 2003).[2] Generally, the existing safety research commonly argues that human behavior plays a vital role in road

* Tel.: +45 353 23010; fax: +45 353 23000.
E-mail address: Kibrom.Araya.Abay@econ.ku.dk.

[1] Worldwide, traffic accidents are the leading causes of death for individuals aged 15–29 years (WHO, 2009a). In Denmark, traffic accidents are the leading causes of 'unintentional injury-caused death' for individuals aged 15–19 years (EuroSafe, 2012). Indisputably, this yields incredible economic and social burden to the overall national economy. For instance, the economic burden of traffic accidents is estimated to be 3% of the country's gross domestic product for most of European countries (WHO, 2009b).

[2] While the earlier findings from these studies have been generally consistent to a large extent, contradicting evidences have been documented with regards to the effect of the gender of pedestrians. Some studies argue that men pedestrians are more susceptible to serious or fatal injuries (Eluru et al., 2008), probably due to their risky walking or crossing behavior (Holland & Hill, 2007). Contrary to this finding, others (Lee & Abdel-Aty, 2005; Sze & Wong, 2007) conclude that women pedestrians are more likely to sustain more fatal injuries, potentially due to men's relative physiological strength compared to women.

0739-8859/$ – see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.retrec.2012.12.002

accidents and their injury severity outcomes. More specifically, some earlier studies argue that driving behavior, particularly aggressive driving, is the leading cause of traffic accidents (see AAA Foundation for Traffic Safety, 2009; Evans, 1993). Thus, educational campaigns and legal enforcement measures that focus on affecting drivers' driving behavior could enhance the 'crash-avoidance' strategies and post-crash evasive measures of drivers. However, though there has been some earlier research on pedestrians' injury severity, the post-crash data used in most of the previous studies do not capture all important aspects of driving, walking and crossing behavior of road users at the time of the crash, due to the limited information available in the usual post-crash accident registers. Econometrically, omitting a relevant explanatory variable, driving (or walking) behavior, which is expected to be potentially correlated with some of the usually controlled road user attributes, can lead to inconsistency of all estimates of the model. From a policy design perspective, omitting a relevant explanatory variable is a grave problem as it could misguide intervention strategies.

Obviously, investigating the vulnerability (or injury severity) of pedestrians and the economic appraisal of pedestrianization heavily relies on an appropriate and more encompassing modeling approach. Some of the restricted econometric injury severity models commonly employed in the safety research could misguide educational campaigns and legal enforcement strategies that address specific safety measure. In terms of modeling the injury severity of traffic accidents, both ordered response and unordered response modeling frameworks have been employed in the earlier safety research. As injury severity levels seem inherently ordered, the ordered response framework can be considered as relatively effective in representing the data generation process, though these models impose some inconvenient restrictions on the data. Similarly, though unordered response models (multinomial, nested and mixed logit) do not capture the ordinal nature of the response outcomes, they allow for flexible variable effects across the successive injury severity levels. This implies that the choice of injury severity modeling approaches involves potential trade-off. Thus, investigating the empirical implications of these modeling approaches, and exploring the sensitivity of the empirical findings to the choice of these models are interesting questions that deserve thoughtful attention. This enables economists and transportation safety policy makers design economically efficient, optimal, coherent and convivial countermeasures that improve the safety of road users.

This paper investigates the injury severity of pedestrians considering detailed road user characteristics and alternative model specification using a high-quality Danish road accident data. It considers exogenous proxies for driving behavior and controls for momentary activities of road users at the time of accidents. This helps to identify road users' activities that are risky to pedestrians, so that alternative policy measures and mobility management strategies can be implemented. Considering some psychological researches on personality and driving behavior, crime history of drivers in the past three years before the accident is captured as a proxy for driving behavior (aggressive driving) at the time of the accident. More succinctly, this research effort adds to the existing safety literature in at least two key directions. First, it extends the research on pedestrian-injury severity considering a more encompassing specification, with exogenous proxies for driving behavior and detailed information on momentary activities of road users at the time of the crash. Second, it employs alternative model specification to investigate the sensitivity of the empirical results to the choice of the *state of the art* injury severity models commonly used in the existing safety literature.

The remaining sections of this paper are organized as follows: Section 2 reviews the two commonly employed injury severity modeling strategies in the existing safety research. Section 3 presents the details of the data, sample description and the variables considered in the empirical analysis. Section 4 presents the econometric approach and estimation strategies. Section 5 presents the estimation results, while Section 6 discusses the empirical findings and Section 7 summarizes the key findings.

2. Review of the existing injury severity modeling practices

In view of the fact that the overall safety and economic implication of injury severity analysis heavily relies on the choice of econometric modeling approaches, this section highlights the commonly used modeling frameworks employed in the earlier safety research. As mentioned in Section 1, there are two widely employed injury severity modeling approaches in the safety research. These models have their own working assumptions and restrictions, which could plausibly yield far-reaching implication on the overall empirical inferences from these models.

2.1. Ordered response framework

From data generation point of view, injury severity outcomes seem inherently ordered. With ordered outcomes, adjacent alternatives are expected to share some common trend depending on their proximity to each other, the closer they are, the larger trend they share (Train, 2009). This potentially implies that adjacent response outcomes could also share some unobservable effects. In view of this fact, some of the standard unordered response models which are built on the assumption that unobserved effects are independent across alternatives, could provide inconsistent estimates when applied to ordered response outcomes. This suggests that considering a modeling framework that accounts for the ordinal nature of response outcomes is crucial when modeling the injury severity of traffic accidents. The aforementioned inherent feature of injury severity data has paved substantial advantage to ordered response models, so that extensive use of this framework to analyze the injury severity of traffic accidents (see, for example, Abdel-Aty, 2003; Christoforou, Cohen, & Karlaftis, 2010; Eluru & Bhat, 2007; Eluru et al., 2008; Kockelman & Kweon, 2002; Pai & Saleh, 2007; Paleti, Eluru, & Bhat, 2010; Quddus, Wang, & Ison, 2010; Srinivasan, 2002; Wang & Abdel-Aty, 2008; Wang & Kockelman, 2005; Zhu & Srinivasan, 2011).[3]

However, there are at least three potentially binding shortcomings associated with the standard ordered response models used in the existing safety research. The first and most grave problem is the monotonicity restriction that the standard ordered response models impose on the data, which guides the way independent variables of the model affect successive probability outcomes (see, for example, Savolainen, Mannering, Lord, & Quddus, 2011; Washington, Karlaftis, & Mannering, 2011). This restriction mainly emanates from the proportionality (parallel-lines) assumption and linearity of the single index of these models. Evidently, this restriction could affect the final empirical inferences and policy implications drawn from the analysis as some variables do not seem to satisfy this assumption empirically.[4] A prominent observation of the fact comes from Boes and

[3] See Table A.2 in the Appendix for a detailed survey of these studies along with the specific analytical framework employed and the key findings from each study.

[4] For example, deployment of air bag decreases the probability of fatal injury while it concurrently decreases the probability of no injury due to the possible scratches from the air bag (Savolainen et al., 2011).

Winkelmann (2006), which documented that marginal effects (partial derivatives) of variables based on the standard ordered response models are 'single crossing' as their sign change only once in the sequence from the lowest to the highest response outcomes. Secondly, it is argued that ordered response models are reasonably sensitive to underreporting of crashes (Ye & Lord, 2011). Thirdly, the standard ordered response models have been commonly employed with fixed thresholds along with fixed effect of the variables across the observations. More specifically, most of the earlier injury severity studies are generally built on the assumption that the effects of explanatory variables considered do not vary across observations.[5] However, it is evident that unobserved road user and crash characteristics could generally moderate the impact of explanatory variables considered. For instance, some studies on non-motorized road users argued that men pedestrians are more susceptible to fatal injuries due their negligent walking behavior compared to women pedestrians. However, there are some men pedestrians who are more safety-conscious when walking and crossing road segments than women pedestrians, so that are more likely to be safe compared to women pedestrians.

2.2. Unordered response framework

Due to the aforementioned restrictions, unordered response models (multinomial, nested and mixed logit) have been alternatively employed in modeling the injury severity of traffic accidents. Though these models do not capture the ordinal nature of the response outcomes, they allow for more flexible variable effects as they do not impose any restriction on the parameters and marginal effects of the variables. Furthermore, it is argued that unordered response models are relatively robust to underreporting of crashes (Ye & Lord, 2011). This is an attractive feature of these models, particularly considering injury severity data, which is subject to underreporting of less severe crashes. Consequently, a sizeable share of the safety research has employed unordered response models to analyze the injury severity of traffic accidents (see Kim, Kim, Ulfarsson, & Porrello, 2007; Kim et al., 2008, 2010; Milton, Shankar, & Mannering, 2008; Moore, Schneider, Savolainen, & Farzaneh, 2011; Savolainen & Mannering, 2007; Shankar, Mannering, & Barfield, 1996; Rifaat, Tay, & de Barros, 2011; Ulfarsson & Mannering, 2004; Yan, Ma, Huang, Abdel-Aty, & Wu, 2011).

However, the standard unordered response models are built on the assumption that unobserved effects are independent across response outcomes, which is inconsistent assumption in view of ordered outcomes (Train, 2009). This assumption is imposed through the independent and identically distributed (IID) assumption of the error terms across alternatives, which in turn yields the independence from irrelevant alternatives (IIA) restriction. This restriction is binding, particularly in view of injury severity modeling for the reason that adjacent injury severity levels are related.

3. Data

3.1. Data source and sample description

This study uses police-reported road accident data from Denmark. The police-reported road crash data contains information on road accidents which involve at least one driving traffic unit. Demographic data such as driver's crime history, driver's marital status and years since driver's driving license issued are drawn from population-register data at Statistics Denmark. Such detailed information on driver's personalities has been missing in almost all existing injury severity studies, though it is strongly believed that such latent personalities substantially explain the driving behavior of drivers. Thus, by linking post-crash data and population-register data, the current data set enables more comprehensive injury severity analysis using extended information set on road users' driving and walking behavior.

This study considers road accidents involving a pedestrian and single motorized vehicle. Specifically, the empirical analysis is confined to pedestrian–motor vehicle crashes that are reported in the years 1998–2009, which counts to be 4952 observations. The police-reported road crash data used in this analysis records pedestrians' injury severity in four ordinal levels as: (1) no injury or no casualty, (2) slight injury, (3) serious injury and (4) killed or fatal injury. The final number of pedestrians who sustained no injury were quite few (less than 2 percent of the overall sample), for which they are merged with those slightly injured in the empirical analysis. Furthermore, theoretically, merging both adjacent injury severity levels is not expected to substantially affect our inferences provided that these adjacent injury categories are also slightly similar. The final sample distribution of pedestrians' injury severity levels is as follows: slight/no injury (37.88%), serious injury (53.96%), and fatal injury (8.18%). Table A.1 provides a cross-tabulation of the frequencies of outcomes for each variable considered in the empirical analysis.

As this study uses police-reported road accidents, it might be argued that the data is subject to underreporting of less severe crashes. However, reporting rate for accidents involving pedestrians is thought to be fairly better than other types of accidents as pedestrians have no any protection material that can reduce the consequences of accidents, and are relatively motivated to report the incident to the police for being compensated (Kim et al., 2008). Evidently, Statistics Denmark assessed the reporting rate of the police-reported accident data compared to the crashes reported to hospitals (casualty wards) and documented that the rate of reporting for accidents involving pedestrians is fairly good compared to other motorized accidents.[6]

3.2. Variables considered

The empirical analysis is built on thorough consideration of potential human and physical factors that could affect the injury severity of pedestrians. It is worth noting that this study analyzes pedestrian's injury severity conditional on the fact that the pedestrian is involved in the crash. This conditionality simplifies the identification of effects of the variables controlled. Unconditional injury severity analysis may involve two-step estimation approaches, which entail predicting the probability of being involved in a crash, and investigating the subsequent injury severity outcome of the crash.

[5] To address the above prominent shortcomings of these models, the econometrics literature has gone some indispensable steps to tackle each problem. To address the single indexing (parallel-lines assumption) nature of these models, generalized ordered models have been proposed (see Williams, 2006) and recently applied in the safety literature (see Quddus et al., 2010; Wang & Abdel-Aty, 2008). Likewise, Eluru et al. (2008) and Castro, Paleti, and Bhat (2012) proposed another comprehensive generalization which accommodates systematically varying thresholds. Furthermore, recently some studies have employed modeling approaches that accommodates unobserved heterogeneity among observations in injury severity models (see, for example, Christoforou et al., 2010; Eluru & Bhat, 2007; Kim et al., 2010; Milton et al., 2008; Moore et al., 2011; Paleti et al., 2010).

[6] See at http://www.statbank.dk/statbank5a/default.asp?w=1280.

Generally, the exogenous variables considered in the empirical analysis can be classified in to the following categories: pedestrian characteristics, driver characteristics, vehicle attributes, environmental characteristics, roadway features, land use features and crash characteristics of the accidents.[7] In view of the above categories, the pedestrian characteristics considered consist of age, gender and alcohol consumption of the pedestrian. In the same vein, the driver demographics considered comprises of the age, gender and alcohol consumption of the driver. Besides to these commonly controlled attributes, the current study considered detailed driver personalities that are plausibly expected to explain the driving behavior of drivers. These include: the drivers' crime history in the past three years before the accident, which is expected to be an exogenous proxy for degree of driving aggressiveness; the length of years since the driving license is issued, which could be a weak proxy for driving experience, and the marital status of drivers. Moreover, momentary activities of pedestrians at the time of accident (crossing using marked crossing, crossing using unmarked crossing, staying in a roadside and side walking) are considered. Correspondingly, a countermeasure of momentary activities of drivers is captured through drivers' maneuver (driving straight-ahead, turning and reversing). The only vehicle characteristic considered in the empirical analysis is the type of the vehicle that struck the pedestrian (private car weighting < 1000 kg, private car weighting ≥ 1000 kg, taxi, van and bus). The environmental factors included consist of the weather (dry weather or adverse weather) and lighting conditions (daylight, dark-lighted and dark-unlighted) at the time of the crash. Roadway characteristics such as road type, state of the road (wet or dry) and the speed limit on the road are also considered in the empirical analysis. Likewise, land use features of the place where the accident occurred are included. Furthermore, crash characteristics such as collision point, accidents at intersections, and traffic unit who failed to give duty (pedestrian only, driver only, both and none) are controlled. Finally, the analysis considered some interaction effects among the variables (e.g., crime involvement and male driver), and some of the continuous variables such as the age of the pedestrians (or drivers) and the speed limit posted on the road were tested for alternative functional forms.

4. Econometric approach and estimation strategies

This research employs a mix of *state of the art* ordered and unordered response models. Thus, the estimation process starts with ordered response models as severity outcomes seem inherently ordered. Furthermore, this study adopts a random parameter specification to accommodate unobserved heterogeneity effects in the impact of variables on the injury severity of pedestrians.

Following the usual ordered response framework, we can specify the latent pedestrian-injury risk propensity ,y_p^*, be a linear function of the observed variables and a stochastic unobserved component as follows:

$$y_p^* = \boldsymbol{\beta}_p'\mathbf{x}_p + \varepsilon_p, \quad y_p = m \quad \text{if } \psi^{m-1} < y_p^* < \psi^m \tag{1}$$

where $\mathbf{x}_p$ is a $(K \times 1)$ vector of exogenous (excluding a constant term) variables that explain pedestrian p's injury severity outcome, $\boldsymbol{\beta}_p$ is the corresponding vector of pedestrian specific coefficients, while ε_p is an idiosyncratic error term which is assumed to be identically and independently standard logistic distributed across pedestrians, and ψ^m is the upper threshold corresponding to injury severity outcome m (with $\psi^0 < \psi^1 < \psi^2 < \psi^3$; $\psi^0 = -\infty, \psi^3 = +\infty$). As usual, the latent injury risk propensity y_p^* is mapped to the actual observed injury severity level y_p using the jointly estimated threshold parameters ψ.

The pedestrian specific parameter vector $\boldsymbol{\beta}_p$ in Equation (1) is assumed to be drawn from a multivariate normal distribution with mean vector $\mathbf{b}$ and covariance matrix $\boldsymbol{\Omega} = \mathbf{LL}'$, where $\mathbf{L}$ stands for the lower triangular matrix of the Cholesky decomposition of $\boldsymbol{\Omega}$. More plainly, we can write $\beta_p = \mathbf{b} + \tilde{\boldsymbol{\beta}}_p$, where $\tilde{\beta}_p$ is multivariate normal distributed with a mean vector of zeros and a covariance matrix $\boldsymbol{\Omega}$. To simplify the complexity of the estimation process (which is also a common specification in the literature), we assume the random parameters to be independent to each other, so that $\boldsymbol{\Omega}$ holds only diagonal elements, which correspond to the variance of the parameters. Obviously, the parameters that can be estimated from Equation (1) are the threshold parameters (ψ^1,ψ^2), mean ($\mathbf{b}$) and covariance of the model parameters ($\boldsymbol{\Omega}$). Following the standard ordered response framework and recalling the distributional assumption on ε_p, we can write the conditional likelihood function for each pedestrian p as given below:

$$\begin{aligned} L_p(\psi, \mathbf{b}, \boldsymbol{\Omega}) &= P\Big(y_p = m\Big) \\ &= \Big\{\Phi(\psi^m - \boldsymbol{\beta}_p\mathbf{x}_p) - \Phi\Big(\psi^{m-1} - \boldsymbol{\beta}_p\mathbf{x}_p\Big)\Big\}^{d_{pm}} \end{aligned} \tag{2}$$

where ψ^m and ψ^{m-1} stands for the upper and lower thresholds, respectively, for injury severity m, while $\Phi(\cdot)$ is the cumulative distribution function, which is standard logistic distribution in the current case, and d_{pm} stands for a dummy variable which assumes a value of 1 if pedestrian p sustains an injury severity level of m and 0 otherwise. The unconditional likelihood function for each pedestrian involves a multi-dimensional integral of dimension equal to the number of random parameters specified as shown below:

$$\begin{aligned} L_p(\psi, \mathbf{b}, \boldsymbol{\Omega}) = \int\limits_{\beta=-\infty}^{\infty} & \Big[\Big\{\Phi(\psi^m - \boldsymbol{\beta}'\mathbf{x}_p) - \Phi\Big(\psi^{m-1} - \boldsymbol{\beta}'\mathbf{x}_p\Big)\Big\} \\ & \times f(\boldsymbol{\beta}|\mathbf{b}, \boldsymbol{\Omega})\mathrm{d}\boldsymbol{\beta}\Big]^{d_{pm}} \end{aligned} \tag{3}$$

where $f(\cdot)$ is multivariate normal density function with mean vector $\mathbf{b}$ and covariance $\boldsymbol{\Omega}$. This integral can be approximated using simulation techniques and the parameters can be estimated using Maximum Simulated Likelihood (MSL) approaches. Thus, we can write the average simulated likelihood function for each pedestrian p across the number of simulation draws as:

$$\widehat{L}_p(\psi, \mathbf{b}, \boldsymbol{\Omega}) = \frac{1}{R}\sum_{r=1}^{R} L_{pr}(\psi, \mathbf{b}, \boldsymbol{\Omega}) \tag{4}$$

where R stands for the total number of draws used, and $L_{pr}(\psi,\mathbf{b},\boldsymbol{\Omega})$ stands for the likelihood contribution of pedestrian p and draw r. The MSL approach then maximizes the sum of logarithm of the average simulated likelihood values across all pedestrians in the sample as shown below:

$$L = \sum_p \log \widehat{L}_p(\psi, \mathbf{b}, \boldsymbol{\Omega}) \tag{5}$$

While evaluating and maximizing the above log-likelihood function with respect to the parameters of the model, Quasi–

[7] Though it is not theoretically straightforward, one could hypothesize the mechanism and channels through which all these variables affect the injury severity outcome of pedestrians. Few studies (Elvik, 2003, 2004) have tried to point out some causal mechanisms through which some important safety measures affect road users' injury severity outcome. Extending these research efforts in to a more comprehensive and structural specification is a future research avenue.

Monte-Carlo (QMC) draws (specifically, Halton draws) are employed consistent with the contemporary simulation-based literature. For a detailed exposition of Halton draws and the different variants of such drawing scheme one can refer Bhat (2001, 2003).

To observe the restrictions of the (standard) ordered logit model, the proportionality (parallel-lines) assumption can be assessed using Brant test (Brant, 1990), for which the result indicates that the assumption is decisively rejected. The frequent rejection of this assumption has induced at least two different solution directions in the existing econometrics literature. The first strategy is ignoring the non-proportionality and continuing with the restricted and more parsimonious ordered response model. The second solution direction is switching to unordered response models. The current analysis considers both solution directions to investigate the performance and implications of each solution strategy.[8] Thus, the next alternative econometric approach involves estimation of unordered response models. As done for the ordered response framework, to accommodate for heterogonous effect of the independent variables across observations (pedestrians), we adopt a random parameter specification, which generally, leads to the mixed logit (MXL) framework. Interestingly, the MXL model specification, in addition to allowing variation in the effect of variables across observations, it relaxes the IID assumption and the IIA restriction (see Train, 2009).

Theoretically, unordered response models are motivated in a slightly different theoretical foundation compared to the ordered response models. Most commonly, the propensity function that determines the probability pedestrian p sustains a specific injury severity category m is specified as a linear function of the observed explanatory variables and a stochastic unobserved component as follows:

$$s^*_{pm} = \boldsymbol{\beta}_{pm}\mathbf{x}_p + \varepsilon_{pm} \tag{6}$$

where $\mathbf{x}_p$ stands for a vector of independent variables considered, and $\boldsymbol{\beta}_{pm}$ is a vector of alternative-specific coefficients which are allowed to vary across observations (pedestrians), while ε_{pm} is a stochastic error term. Obviously, the individual specific vector of alternative-specific parameters $\boldsymbol{\beta}_{pm}$ can be written as $\boldsymbol{\beta}_{pm} = \mathbf{b}_m + \tilde{\boldsymbol{\beta}}_{pm}$, where $\tilde{\boldsymbol{\beta}}_{pm}$ is multivariate normal distributed with a mean vector of zeros and a covariance matrix of $\boldsymbol{\Omega}_m$. If the error terms, ε_{pm}, are assumed to be identically and independently distributed extreme value, we can write the unconditional likelihood contribution of pedestrian p sustaining injury severity level m following the usual multinomial probability outcome (see McFadden, 1981; McFadden & Train, 2000):

$$L_p(\mathbf{b}_m, \boldsymbol{\Omega}_m) = P(s_p = m) = \int\limits_{\boldsymbol{\beta}_m=-\infty}^{\infty} \frac{\exp(\boldsymbol{\beta}_m\mathbf{x}_p)}{\sum_{m=1}^{M}\exp(\boldsymbol{\beta}_m\mathbf{x}_p)} f(\boldsymbol{\beta}_m|\mathbf{b}_m, \boldsymbol{\Omega}_m)\mathrm{d}\boldsymbol{\beta}_m \tag{7}$$

where $f(\cdot)$ is multivariate normal density function with mean vector $\mathbf{b}_m$ and covariance $\boldsymbol{\Omega}_m$. Noticeably, computing the above probability entails evaluating a multi-dimensional integral of size equal to the number of random parameters specified. Similar to the ordered response framework discussed above, this multi-dimensional integral can be approximated using simulation techniques and the parameters ($\mathbf{b}_m$ and $\boldsymbol{\Omega}_m$) can be estimated using the MSL approaches.

Generally, while maximizing the above log-likelihood functions (for both ordered and unordered response models) using MSL approach there are some practical non-trivial estimation issues that deserve attention: first, initially all variable effects of the models were tested to be randomly distributed, and finally parameters of the model for which their estimated standard deviations are statistically insignificant are kept to be fixed. In view of choice of distributional forms for the random parameters, the normal distribution is chosen in congruent with some earlier injury severity studies (see, for example, Milton et al., 2008; Moore et al., 2011). Second, to ensure the positive definiteness of $\boldsymbol{\Omega}$ and $\boldsymbol{\Omega}_m$ the likelihood function is parameterized in terms of the Cholesky decomposed matrix components $\mathbf{L}$ and $\mathbf{L}_m$, respectively, which in the current case stands for the standard deviation of the parameters. Obviously, if all the standard deviation parameters in $\boldsymbol{\Omega}$ and $\boldsymbol{\Omega}_m$ are not statistically significant, our random parameters models (RPOL and MXL) collapses to the fixed-parameters models, standard ordered logit (OL) and standard multinomial logit (MNL) models, respectively. Third, considering the simulation noise which is evident when using finite number of draws, standard errors of the parameters are estimated using the inverse of the sandwich information matrix (commonly referred to as robust standard errors; see McFadden & Train, 2000).

5. Estimation results

Totally, this study estimated four different models: the standard fixed-parameters ordered logit (OL), the random parameters ordered logit (RPOL), the standard fixed-parameters multinomial logit (MNL) and the random parameter multinomial logit or mixed logit (MXL) model. The final specification for each model presented in this section is found by excluding statistically insignificant variables. For simplicity, in this section, only the estimates for the random parameter models (RPOL and MXL) are presented. The overall fit of the models can be judged by computing McFadden's adjusted-ρ^2. This measure compares the models' log-likelihood value at convergence with the log-likelihood value of a naive model with all coefficients set to zero (equivalent to assigning equal probability to all outcomes), corrected for the number of parameters estimated.[9] In general, the overall fit of the models is satisfactory. Table 1 presents the estimates only for the random parameter models.

Though ordered and unordered response models are not nested to each other, comparison of the overall performance of these models and investigating the empirical implications from these models is plausible. To judge the comparative performance of those models which are nested to each other, we can compute the likelihood ratio test. Likewise, models which are not nested to each other can be compared using AIC (Akaike Information Criterion) as well as McFadden's adjusted-ρ^2. However, a simple comparison of

[8] Another approach, which is relatively lenient strategy, is to relax the proportionality assumption through Williams's (2006) Generalized Ordered Logit (GOL) model. Therefore, following Williams (2006), the current analysis considered the GOL model as another alternative approach in the empirical estimation process. This model is equivalent to the standard ordered logit model except the fact that $\boldsymbol{\beta}$ is not fixed across severity outcomes or equations. However, the theoretical foundation of the model is not clear and the relationship between the latent variable outcome and the actual injury severity outcome cannot be mapped unambiguously (Greene & Hensher, 2010, pp. 147–160). Likewise, negative probabilities are theoretically unavoidable in this specification. Furthermore, we noticed that the overall implications from this model are comparable with the unordered multinomial logit framework. Therefore, results from this model will not be presented here but can be found from the author up on request.

[9] More explicitly, McF adden adjusted-$\rho^2 = 1-(ll(\beta)-K)/(ll(0))$, where $ll(\beta)$refers to the log-likelihood value at convergence, $ll(0)$stands for the log-likelihood value at zero while K refers to the number of parameters estimated and $AIC = -2ll(\beta) + 2K$, where K refers to the number of parameters estimated and the smallest is the better (see Washington et al., 2011).

Table 1
Estimated coefficients in the two random parameters models (RPOL and MXL).

Variables considered	RPOL model estimates	MXL model estimates	
		Fatal injury	Serious injury
Pedestrian characteristics			
Gender (1 = male)	0.199 (2.36)	0.260 (1.74)	0.093 (1.15)
Standard deviation	0.830 (3.81)		
Under the influence of alcohol	0.537 (3.82)	0.798 (4.40)	0.302 (1.62)
Standard deviation	1.382 (5.86)		1.730 (1.67)
Age: young ($15 \leq$ age ≤ 35)	−0.281 (−2.78)	−0.508 (−2.76)	−0.216 (−2.20)
Standard deviation	0.612 (2.17)		
Old-aged (age ≥ 60)	1.252 (10.78)	1.918 (11.13)	0.802 (8.13)
Standard deviation	1.132 (5.33)		
Driver characteristics			
Age: young	0.173 (1.69)	0.172 (0.99)	0.192 (1.86)
Mid-aged inexperienced	0.279 (2.86)	0.408 (2.42)	0.180 (1.94)
Standard deviation	0.564 (2.15)		
Under the influence of alcohol	0.239 (0.82)	0.908 (3.20)	−0.244 (−1.11)
Standard deviation	2.092 (4.24)		
Male driver with crime history	0.215 (2.10)	0.601 (3.78)	0.016 (0.166)
Standard deviation	0.855 (2.57)		
Environmental characteristics			
Lighting: dark-lighted	0.308 (3.41)	0.756 (4.40)	0.166 (1.93)
Dark-unlighted	1.252 (6.32)	1.579 (7.16)	0.181 (0.83)
Vehicle characteristics			
Bus	0.675 (4.38)	1.321 (1.86)	0.176 (1.30)
Standard deviation		3.793 (2.62)	
Roadway characteristics			
Speed limit: high (speed limit > 50)	0.549 (4.72)	0.841 (4.58)	0.312 (2.74)
Land use			
Areas with no building	0.292 (2.29)	0.866 (4.39)	0.063 (0.37)
Standard deviation			2.273 (1.76)
Pedestrian activities			
Crossing through unmarked crossing	0.387 (4.20)	0.370 (2.09)	0.462 (3.20)
Standard deviation			1.585 (2.09)
Pedestrian staying in roadside	0.633 (4.56)	1.138 (5.37)	0.277 (2.26)
Driver's maneuver			
Driving straight-ahead	0.327 (3.21)	1.100 (4.12)	0.190 (1.96)
Standard deviation	1.219 (6.13)		
Crash characteristics			
Accidents at intersections	0.146 (1.37)	0.459 (2.48)	−0.006 (−0.06)
Pedestrian failed to give duty	0.292 (2.04)	0.195 (0.73)	0.400 (2.58)
ψ^1	−0.843 (−7.83)		
ψ^2	−5.350 (−16.68)		
ASC		−5.386 (−17.91)	−0.471 (−4.50)
Log-likelihood value at convergence	−4173.10	−4107.30	
Log-likelihood value at fixed parameters	−4202.65	−4120.00	
Log-likelihood value at zero	−5440.00	−5440.00	
Brant test-χ^2 (p-value)	164.66 (0.0001)		
McFadden's adjusted-ρ^2	0.238	0.253	
AIC	8402.10	8298.60	
Number of observations	4952	4952	

T-values are in parenthesis and ASC stands for alternative-specific constant. For the MXL model estimates those pedestrians who sustained slight/no injury are used as base outcome.

fit of ordered response and unordered response models is not insightful as the latter models estimate exceedingly large number of parameters than the former models. Thus, investigating the pattern and trend of marginal effects of the variables across both models is more intuitive and insightful. This comparison enables us to detect the restrictions and empirical implication of the standard ordered response models. Provided that the unordered response models estimate almost twice parameters as the ordered response models in the current case, it appears that the fit of the former models is better than the latter models (as can be seen from the McFadden's adjusted-ρ^2 and the AIC). However, such a comparison is of first instance, and as the theoretical derivation of these models is slightly different, this finding needs further research to validate the conclusion. Furthermore, the fact that this analysis considers only three injury outcomes (alternatives) might not be sufficient to visibly reveal the comparative performance of these models. One could investigate the relative performance of these models considering a larger set of ordered outcomes either using simulated or real data.

The log-likelihood values at convergence for the OL, RPOL, MNL and MXL models are −4203, −4173, −4120 and −4107, respectively. The RPOL model has eight more parameters than the OL model. Likewise, the MXL model has four more parameters than the MNL model. Thus, a likelihood ratio test statistic for reduction from the RPOL to OL model turns out a value 59, which is larger than the tabulated chi-square value with eight degrees of freedom at any reasonable level of significance. Similarly, the likelihood ratio test for a reduction from the MXL specification to the MNL specification turns out a value of 25, which is still larger than the tabulated chi-square value with four degrees of freedom at the conventionally used level of significance. Unquestionably, this implies that the RPOL and MXL models provide superior fit than their fixed-parameters variants, OL and MNL models, respectively. This evidence suggests the need to account for potential unobserved heterogeneity which could moderate the effect of the explanatory variables considered in the econometric application. Obviously, estimates of the random parameters models (RPOL and MXL) and the fixed-parameters models (OL and MNL) are not directly comparable since these estimates are scaled differently across these models. Moreover, the comparative advantage of the random parameters models should not be weighed in terms of the specific parameter estimates and fit of the models, but in the additional intuitive evidence provided through the mean and standard deviation of the parameters. For instance, according to the RPOL model, men pedestrians are likely to sustain fatal injuries than their women peers in 60% of the crashes (sample), while the reverse happens in 40% of the crashes. This evidence could be associated with the fact that some men pedestrians are more safety-conscious when walking and crossing through road segments than women pedestrians. Likewise, according to the RPOL model, the parameter for old-aged pedestrians is less than zero in 13% of the sample. This finding could be attributable to the fact that some old-aged pedestrians are physically robust compared to their mid-aged peers (the base outcome). Similarly, according to the MXL model, the parameter for crossing with unmarked crossing is less than zero in 39% of the cases in our sample. This is also appealing as some pedestrians crossing with unmarked crossing (non-crosswalks) could take risk compensating and extra precaution when crossing roads as they perceive violating traffic rules. These evidences assure that assuming fixed effect of variables for all pedestrians in the sample could ignore some unobserved heterogeneity among pedestrians. These findings on the distribution of the parameters have been masked under the fixed-parameter specification, an issue which could potentially bias our inferences and misguide safety measures.

5.1. Marginal effects of the variables across the models

The estimated coefficients in Table 1, do not directly indicate the magnitude of the effect of the variables considered in the empirical analysis. Furthermore, to facilitate the comparison of effects of the variables across the different models estimated, we can compute marginal effects. The marginal effects computed here, are simply the average percentage change in the probability of an injury severity category when a variable switches (from 0 to 1) for all observations. To compare the pattern of marginal effects across the different models estimated in the analysis, we compute the mean and standard deviations of the marginal effects across 200 bootstrap draws taken from the sampling distribution of the estimated parameters in each model. For presentational ease, Table 2, reports the marginal effects (and their standard deviations) for the OL and the two random parameters models only (RPOL and MXL). The entries in the table can be interpreted as the average percentage change in the probability of a specific injury category due to the change in one of the independent explanatory variables in the model. For instance, the first entry in the table indicates that according to the OL model, men pedestrians are 16% (with a standard deviation of 7%) more likely to sustain fatal injury compared to women pedestrians.

As can be clearly seen from Table 2, there appears substantial differences in the marginal effect of the variables in the standard OL and the other two random parameters models (RPOL and MXL). For instance, considering a single fatal injury category, the standard OL model revealed a substantially lower marginal effect for the variables pedestrian under the influence of alcohol, and driver under the influence of alcohol, compared to the RPOL and MXL models (the differences in marginal effects across the models for these variables are statistically significant at 0.0001 significance level). Unequivocally, such underestimation misinforms safety planners on the potential risk of driving and walking under the influence of

Table 2
Marginal effects of the variables in the three models estimated.

Variables considered	Ordered logit (OL)			Random parameter ordered logit (RPOL)			Mixed logit (MXL)		
	Fatal injury	Serious injury	Slight/no injury	Fatal injury	Serious injury	Slight/no injury	Fatal injury	Serious injury	Slight/no injury
Pedestrian characteristics									
Gender (1 = male)	15.84 (6.97)	4.79 (2.05)	−9.33 (3.79)	40.91 (14.89)	1.63 (2.47)	−5.42 (4.12)	20.92 (15.23)	1.71 (3.1)	−5.9 (3.53)
Under the influence of alcohol	42.5 (11.57)	10.57 (2.53)	−22.11 (4.94)	133.99 (40.95)	1.68 (3.58)	−14.32 (5.35)	88.1 (33.44)	3.92 (6.27)	−14.99 (8.22)
Age: young ($15 \leq$ age ≤ 35)	−18.79 (6.31)	−6.79 (2.61)	15.16 (5.68)	−11.15 (11.4)	−7.64 (2.7)	15.34 (5.74)	−29.93 (11.11)	−5.47 (3.79)	16.39 (5.81)
Old-aged (age ≥ 60)	131.02 (14.40)	27 (3.92)	−45.18 (3.15)	268.76 (54.92)	20.06 (5.63)	−39.71 (4.26)	281.98 (61.67)	18.5 (5.26)	−43.56 (4.68)
Driver characteristics									
Age: young	12.2 (7.85)	3.54 (2.21)	−7.41 (4.59)	13.9 (8.96)	3.54 (2.22)	−7.14 (4.45)	9.83 (16.47)	5.55 (3.71)	−9.11 (4.39)
Mid-aged inexperienced	19.98 (7.91)	5.72 (2.17)	−11.65 (4.12)	36.27 (14.4)	4.18 (2.68)	−9.75 (4.35)	34.35 (18.79)	3.97 (3.3)	−11.18 (3.89)
Under the influence of alcohol	22.44 (19.4)	5.57 (4.51)	−12.3 (9.87)	182.4 (93.73)	−11.65 (7.15)	4.41 (11.65)	142.08 (58.40)	−15.37 (8.65)	−1.13 (9.13)
Male driver with crime history	17.12 (6.97)	4.93 (1.92)	−10.2 (3.84)	46.04 (21.38)	1.35 (2.9)	−6.04 (4.46)	65.22 (24.02)	−2.67 (3.72)	−7.24 (4.60)
Environmental characteristics									
Lighting: dark-lighted	22.24 (7.14)	6.43 (1.99)	−12.76 (3.73)	25.64 (8.43)	6.45 (2.04)	−12.36 (3.68)	76.97 (28.67)	2.12 (3.42)	−13.89 (4.03)
Dark-unlighted	127.83 (23.32)	20.15 (3.75)	−47.05 (5.18)	156.34 (35.69)	21.00 (4.34)	−46.91 (6.25)	254.38 (72.19)	−5.05 (8.01)	−23.98 (8.03)
Vehicle characteristics									
Bus	52.62 (12.66)	12.21 (2.67)	−26.22 (4.87)	67.74 (18.28)	13.36 (3.14)	−27.45 (5.48)	58.52 (24.59)	14.83 (9.36)	−25.71 (10.46)
Roadway characteristics									
High speed limit (>50 kmh)	40.98 (10.67)	10.71 (2.53)	−21.22 (4.55)	50.29 (13.91)	11.26 (2.78)	−21.43 (4.67)	84.95 (33.19)	6.66 (3.93)	−20.29 (4.59)
Land use features									
Areas with no building	27.48 (10.46)	7.48 (2.7)	−15.33 (5.00)	24.04 (11.87)	5.88 (2.77)	−11.66 (5.09)	117.20 (43.25)	−3.40 (5.20)	−7.50 (7.62)
Pedestrian's activities									
Crossing using unmarked cross	30.15 (8.01)	8.79 (2.16)	−16.25 (3.76)	34.66 (9.72)	8.69 (2.24)	−15.59 (3.78)	21.19 (20.97)	14.02 (6.64)	−17.04 (6.62)
Pedestrian staying in roadside	57.23 (13.38)	13.19 (2.96)	−27.76 (4.81)	61.94 (16.52)	12.67 (3.15)	−25.61 (5.08)	136.62 (44.11)	2.47 (5.57)	−22.46 (5.9)
Driver's maneuver									
Driving straight-ahead	29.15 (8.73)	9.03 (2.33)	−15.36 (4.06)	106.85 (29.5)	2.97 (3.23)	−8.54 (4.3)	158.97 (66.05)	1.73 (4.23)	−15.02 (4.74)
Crash characteristics									
Accidents at intersections	10.59 (6.54)	3.18 (1.93)	−6.49 (3.81)	12.45 (7.91)	3.25 (2.02)	−6.42 (3.87)	50.18 (26.75)	−2.42 (3.86)	−4.82 (5.03)
Pedestrian failed to give duty	23.55 (11.39)	6.30 (2.84)	−13.47 (5.87)	23.79 (12.53)	5.67 (2.82)	−11.68 (5.59)	4.66 (24.93)	12.69 (5.99)	−17.25 (5.99)

Values outside parenthesis are mean estimates for the 200 bootstrap draws and standard deviations are in parenthesis.

alcohol. For instance, such underestimation misguides educational and legal campaigns that inhibit DUI (driving under the influence of alcohol). Similarly, for the same injury category, the standard OL model underestimates: the effect of a pedestrian being old-aged (age $\geq$ 60 years), and the effect of a pedestrian being struck by a driver driving straight-ahead (the differences in marginal effects across the OL and RPOL models for these variables are statistically significant at the usually used significance levels). Generally, this underestimation of effects of the variables misguides policy interventions that aim at improving the safety of road users, in general, and those of vulnerable road users, in particular. Comparing the marginal effects from the RPOL and MXL models (for the fatal injury category), it appears that the difference gets smaller but still there are statistically significant differences for some of the variables (driver under the influence of alcohol, driver driving straight-ahead, dark-unlighted). This evidence asserts that safety researchers should employ alternative and appropriate injury severity modeling approaches to investigate the injury severity of traffic accidents.

The fact that we have only single index and one estimate for each variable in the standard OL model reveals that effects of the variables seem reasonably distributed across the successive injury severity outcomes. The RPOL and MXL model can slightly accommodate flexible variable effects across successive outcomes, so that the significance of marginal effects of the variables in these models considerably vary across successive injury severity outcomes unlike in the standard OL model. Furthermore, the pattern of marginal effects of the variables in the above models reveals some vital evidences on the sensitivity of the empirical findings to the choice of these models. A noticeable observation in this regard is that the standard OL model forced some important variable effects to be statistically insignificant while they remain significant predictors in the other two models. This is unfortunate, particularly as the variables excluded seem key attributes such as the alcohol consumption of the driver. Intuitively, marginal effects of the variable, driver under the influence of alcohol, exhibit some reversal effects in the last two flexible model specifications (RPOL and MXL). Such double crossing variable effects cannot be accommodated in the standard OL model due to the monotonicity restriction imposed on the data. More stunningly, Eluru et al. (2008) observed a similar pattern for the same variable, driver under the influence of alcohol.

To sum up, marginal effects of the two generalized models exhibit relatively flexible pattern compared to that of the standard OL model. These evidences generally infer that an empirical specification based on the standard ordered logit model could lead to incomplete and erroneous inferences. Intuitively, such misleading and incomplete conclusions potentially misguide policy measures that target at improving road safety. Therefore, safety researchers should consider more encompassing, flexible and alternative model specification when analyzing injury severity data. This enables transport economists and traffic engineers design more convivial safety measures.

6. Discussion on the empirical findings

This section presents an extended discussion on the empirical findings. The findings in this analysis can be reasonably interpreted considering the estimates and marginal effects of the variables from either of the random parameters models (RPOL and MXL).

6.1. Pedestrian characteristics

The analysis reveals that old-aged pedestrians (age $\geq$ 60 years old) are more likely to sustain fatal injuries. This could be attributed to the physical strength of pedestrians in absorbing impact forces as old-aged individuals are physically frail. Analogous findings are observed in Eluru et al. (2008) and Kim et al. (2008). Likewise, men pedestrians are more likely to sustain fatal injuries. This evidence could be attributed to the gender disparity in risk perceiving and risk taking behavior when walking and crossing in roadside. For instance, Holland and Hill (2007) reported that men pedestrians are more risk takers (perceive less risk) compared to women when crossing roads. Likewise, as pedestrians under the influence of alcohol are expected to walk and cross wildly, they are more likely to sustain fatal injuries. This finding is also in congruent to some earlier studies (see Eluru et al., 2008; Zajac & Ivan, 2003). More intuitively, this finding assures that transport economists and safety planners who are keen at improving the safety of road users need to educate vulnerable road users on the potential risk of walking under the influence of alcohol. Furthermore, transport economists and other safety policy makers that promote pedestrianization need to account for the potential burden of traffic accidents on vulnerable road users such as old-aged pedestrians and pedestrians under the influence of alcohol. On the other hand, public safety policy makers might need to design infrastructural facilities that consider the aforementioned vulnerable road users.

6.2. Driver characteristics

The significant driver characteristics appear to be the gender, age, alcohol consumption and crime history of drivers. Those pedestrians who are struck by drivers who are mid-aged (25–50 years old) and with a driving experience less than 15 years are more likely to be fatally injured. This finding could be attributed to the negligent and aggressive driving behavior of novice drivers. As anticipated, pedestrians hit by drivers under the influence of alcohol are more prone to be fatally injured. The crime involvement (crime history) variable is an indicator variable for drivers with some criminal record in the past three years before the accident. It includes traffic and non-traffic offenses which resulted in ticket fines by the police, suspension of driver's license and other court sentences. The fact that men drivers account for 73% of our sample, yielded that men are the ones that are frequently involved in crimes in the sample. Thus in addition to the main effect, an interaction effect of male driver and driver's involvement in crime is introduced in the specification. Once, we controlled for this interaction effect in the specification, the original gender effect turned out to be statistically insignificant. This implies that the gender effect is statistically insignificant for those drivers who have no any registered crime history. This could be associated with the aggressive driving behavior of drivers with some crime history. Intuitively, this finding provides an important insight to some previous studies which generally concluded that male drivers are probably more aggressive and risk taking drivers so that induce pedestrians to be fatally injured (e.g., Kim et al., 2008, 2010). More generally, this evidence provides an interesting intuition to transport economists and practitioners on the relation between personality and driving behavior. From a policy design perspective, the results highlight need for more tight and tough legal enforcement measures on drivers who exhibit negligent and aggressive driving behavior.

6.3. Momentary activities of road users

It appears that pedestrians staying in roadsides are more likely to sustain fatal injuries. This could be due to the fact that pedestrians waiting in roadsides might not be attentive and ready for any evasive measures up on involvement in a crash. Likewise, pedestrians crossing with unmarked crossings (non-crosswalks) are more likely to be seriously or fatally injured. Not surprisingly, pedestrians struck by drivers driving straight-ahead are more likely to sustain fatal injury since drivers driving straight-ahead are likely to be speeding. Generally, these findings suggest that transport economists and other policy makers that are keen at improving road safety need to put substantial emphasis on affecting road users' attitudes, particularly road users' driving, walking and crossing behavior. Likewise, public safety official might need to invest on infrastructural facilities such as safer crossing and staying facilities for pedestrians. Such countermeasures could yield ultimate effect on the safety of vulnerable road users as these direct measures improve the synergy of the mobility and minimize the vulnerability of road users at a pre-crash phase.

6.4. Vehicle types

As expected, pedestrians hit by bus (lorry) are more likely to be fatally injured. This is not surprising as these vehicles have relatively larger mass and damaging angles. Empirically, it is argued that larger mass vehicles reduce occupants' risk while they endanger the risk of other road users outside the vehicle (see, for example, Abay, Paleti, & Bhat, 2012). This evidence suggests that vehicle manufacturers should invest on safety technology which produces vehicle designs that are both safer to occupants and less damaging to other road users outside the vehicle.

6.5. Environmental characteristics

The significant environmental attribute that is found to be affecting the injury severity of pedestrians is the lighting condition during the accident. The lighting condition (captured by darkness with streetlights as well as without streetlights) increases the likelihood of pedestrians being fatally injured. Furthermore, the size of the marginal effect of the variable, darkness without streetlight (dark-unlighted), is considerably large. This finding deserves substantial attention as some municipalities in Denmark are believed to be practicing some light (energy) saving strategies by turning-off streetlights at some subsidiary roads during nights. Generally, this evidence suggests the need to improve road users' awareness with regards to the risk of driving at nights on the one side, and improving the lighting conditions of roads on the other side.

6.6. Roadway characteristics

Pedestrians involved in accidents at roads with high speed limit (above 50 kmh) are more likely to sustain serious or fatal injuries. The size of the marginal effects of this variable also needs some attention, which potentially implies the power of the information contained in the variable. This is not surprising as the speed limit can be thought as a proxy for the actual speed at the time of the crash. This vibrant evidence suggests that traffic control signals such as speed limit should be designed carefully considering vulnerable road users. On the other hand, drivers and pedestrians should take good care when driving, walking and crossing in roads with higher posted speed limit. Analogous findings have been documented in some of the previous non-motorist injury severity studies (Ballesteros et al., 2004; Eluru et al., 2008; Lee & Abdel-Aty, 2005).

6.7. Crash characteristics

It appears that crashes occurred at intersections are more likely to induce fatal injuries to pedestrians. This is plausibly anticipated, as intersections are more complex road segments that can worsen pedestrian's injury severity. This plainly implies that control signals in such road segments need to be more informative, and road users should be more cautious when using intersections. Likewise, accidents involving pedestrian faults are more likely to yield serious or fatal injuries to pedestrians. This is theoretically expected as such faults affects pedestrian's vulnerability.

Finally, marginal effects from the land use category of the variables reveals that crashes occurred at areas with no building leads to higher likelihood of fatal injuries. This finding is reasonably appealing as drivers might be speeding in such road segments. More generally, this finding is in congruent to some of aggregate studies in the safety research which documented that per capita fatality rate declines with urbanization.

7. Conclusions

This paper investigates the injury severity of pedestrians considering detailed road user characteristics and alternative model specification using a high-quality Danish road accident data. Such detailed and alternative modeling approach helps to assess the sensitivity of empirical inferences to the choice of these models.

There are some key findings evident from the empirical analysis. First, it appears that detailed road user characteristics such as crime history of drivers, the time since the driver got his/her driver license and momentary activities of road users immediately before the crash provided an interesting intuition in the injury severity analysis. For instance, the empirical analysis revealed that pedestrians hit by male drivers with some crime history are more likely to be fatally injured, probably due to the aggressive driving behavior associated with such drivers. This finding confirms the hypothesis that drivers who have some criminal history are more likely to be aggressive drivers. Furthermore, this evidence provides an interesting insight to transport economists and practitioners on the relationship between personality and driving outcome. In line with this, pedestrians staying in roadsides and those hit by drivers driving straight-ahead are more likely to be fatally injured. Generally, these empirical findings assure that pedestrian-injury severity analysis should consider detailed personalities of drivers and momentary activities of road users at the time of accidents. The effects of such attributes have not been well investigated in the previous safety literature due to the limited information available in accident registers. From a policy design perspective, the empirical findings in this analysis suggest that economists and safety planners that are keen at improving road safety or other policy makers who advocate pedestrianization need to put substantial emphasis on affecting road user's attitudes, particularly with regard to road user's driving and walking behavior. Such policy measures can plausibly yield ultimate effects on the safety of road users as these direct measures improve the conviviality of the mobility. Moreover, public safety officials working on economic appraisal of pedestrianization measures should consider vulnerable pedestrians and risky road user activities at the event of crashes.

Second, the comparative analysis of the models reveals that the random parameters models (RPOL and MXL) outperformed their standard fixed-parameters variants (OL and MNL), and provided additional intuitive insight on the distribution of parameters in the empirical analysis. This evidence suggests the need to account for potential unobserved heterogeneity across pedestrians that could moderate the effect of explanatory variables considered in the econometric analysis. Ignoring such subtle unobserved heterogeneity across pedestrians could provide incomplete and erroneous statistical inferences. For instance, considering a single fatal injury category, the standard ordered logit model revealed substantially lower marginal effects for the variables: pedestrian being under the influence of alcohol, and driver being under the influence of alcohol, compared to the random parameters models (RPOL and

MXL). Indisputably, such underestimation misinforms transport economists and other policy makers on the potential risk of driving and walking under the influence of alcohol. The fact that we have only single index and one estimate for each variable in the standard ordered logit (OL) model reveals that effects of the variables seem reasonably distributed across the successive injury severity outcomes. The random parameters models (RPOL and MXL) can accommodate relatively flexible variable effects across successive outcomes, so that the marginal effects (and their statistical significance) of the variables considerably vary across successive severity outcomes unlike in the standard OL model. Furthermore, the pattern of marginal effects of the variables in the alternative models reveals some vital evidences on the sensitivity of the empirical findings to the choice of these models. A noticeable observation in this regard is that the standard OL model forced some important variable effects to be statistically insignificant while they remain significant predictors in the other two models.

Overall, there exist substantial differences in the marginal effects of the variables in the standard ordered logit and the other relatively flexible models, which could be a good signal of the inconvenient restrictions of the standard OL model. Marginal effects of the two generalized models (RPOL and MXL) exhibit relatively flexible pattern compared to that of the standard OL model. These evidences generally infer that an empirical specification based on the standard ordered logit model could lead to incomplete and erroneous inferences. Unequivocally, such misleading and incomplete conclusions potentially misguide policy measures that target at improving road safety. Therefore, transport economists and safety researchers should consider more encompassing, flexible and alternative model specification when analyzing injury severity data. This enables policy makers design economically efficient, coherent and convivial safety measures.

Lastly, most of the remaining empirical findings with regard to the important variables considered in the empirical analysis are in congruent to the previous non-motorist injury severity studies. More succinctly, factors that increase the risk of fatal injury for pedestrians include: being old-aged pedestrian, being male pedestrian, walking under the influence of alcohol, crossing using unmarked crossing (non-crosswalks), waiting in roadsides, being struck by a driver under the influence of alcohol, being struck by a male driver with crime history, being struck by a driver driving straight-ahead and heavier vehicles, crashes at night, crashes at roads with higher speed limit and crashes in areas with no building.

Acknowledgments

The author gratefully acknowledges the helpful comments of two anonymous reviewers and the editor (Ian Savage) on an earlier version of the paper. The author also acknowledges the comments from Mette Ejrnæs, Bertel Schjerning and Carlo Giacomo Prato. The author would also like to acknowledge the Department of Economics (University of Copenhagen) and the Department of Transport (Technical University of Denmark) who jointly financed the project. The usual disclaimer applies.

Appendix

Table A.1
Descriptive statistics of the variables considered.

Variables considered	Total	Fatal injury	Serious injury	Slight/no injury
Total	4952 (100.00)	405 (8.18)	2672 (53.96)	1875 (37.88)
Pedestrian characteristics				
Gender (1 = male)	2462 (49.72)	254 (10.32)	1335 (54.22)	873 (35.46)
Under the influence of alcohol	742 (14.98)	125 (16.85)	399 (53.77)	218 (29.38)
Age: child (age < 15)	825 (16.66)	23 (2.79)	425 (51.52)	377 (45.70)
Young (15 ≤ age < 35)	1384 (27.95)	94 (6.79)	690 (49.86)	600 (43.35)
Mid-aged (35 ≤ age < 60)[a]	1205 (24.33)	104 (8.63)	633 (52.53)	468 (38.84)
Old-aged (age ≥ 60)	1538 (31.06)	184 (11.96)	924 (60.08)	430 (27.96)
Pedestrian's activities:				
Crossing road using marked crossing	1385 (27.97)	53 (3.83)	710 (51.26)	622 (44.91)
Crossing road using unmarked crossing	2267 (45.78)	194 (8.56)	1290 (56.90)	783 (34.54)
Pedestrian staying in roadside	613 (12.38)	102 (16.64)	313 (51.06)	198 (32.30)
Side walking[a]	687 (13.87)	56 (8.15)	359 (52.26)	272 (39.59)
Driver characteristics				
Gender (1 = male)	3632 (73.34)	328 (9.03)	1952 (53.74)	1352 (37.22)
Crime involvement in the past 3 years	1209 (24.41)	126 (10.42)	647 (53.52)	436 (36.06)
Male driver with crime history	1069 (21.59)	119 (11.13)	572 (53.51)	378 (35.36)
Under the influence of alcohol	171 (3.45)	29 (16.96)	77 (45.03)	65 (38.01)
Experience (years since license issued): inexperienced (less than 15 years)	2380 (48.06)	200 (8.4)	1330 (55.88)	850 (35.71)
Experienced (15 years or more)	2572 (51.94)	205 (7.97)	1342 (52.18)	1025 (39.85)
Age: young (age ≤ 25)	1041 (21.02)	91 (8.74)	577 (55.43)	373 (35.83)
Mid-aged inexperienced (25 < age ≤ 50)	1206 (24.35)	102 (8.46)	674 (55.89)	430 (35.66)
Mid-aged experienced (25 < age ≤ 50)[a]	877 (17.71)	79 (9.01)	458 (52.22)	340 (38.77)
Old-aged inexperienced (age > 50)	133 (2.69)	7 (5.26)	79 (59.40)	47 (35.34)
Old-aged experienced (age > 50)	1695 (34.23)	126 (7.43)	884 (52.15)	685 (40.41)
Marital status				
Married	2237 (45.17)	182 (8.14)	1225 (54.76)	830 (37.1)
Married and have a child	974 (19.67)	69 (7.08)	528 (54.21)	377 (38.71)
Driver's maneuver				
Driving straight-ahead	3584 (72.37)	355 (9.91)	1953 (54.49)	1276 (35.60)
Turning[a]	859 (17.35)	28 (3.26)	428 (49.83)	403 (46.92)
Reversing	509 (10.28)	22 (4.32)	291 (57.17)	196 (38.51)

Table A.1 (*continued*)

Variables considered	Total	Fatal injury	Serious injury	Slight/no injury
Environmental characteristics				
Weather: adverse weather	966 (19.51)	93 (9.63)	512 (53.00)	361 (37.37)
Lighting: dark-lighted	1603 (32.37)	127 (7.92)	888 (55.4)	588 (36.68)
Dark-unlighted	480 (9.69)	137 (28.54)	229 (47.71)	114 (23.75)
Vehicle characteristics				
Private car with weight < 1000 kg[a]	1497 (30.23)	113 (7.55)	791 (52.84)	593 (39.61)
Private car with weight ≥ 1000 kg	2369 (47.84)	169 (7.13)	1306 (55.13)	894 (37.74)
Taxi	205 (4.14)	12 (5.85)	121 (59.02)	72 (35.12)
Van	421 (8.50)	46 (10.93)	217 (51.54)	158 (37.53)
Bus (lorry)	460 (9.29)	65 (14.13)	237 (51.52)	158 (34.35)
Roadway characteristics				
Road type: two way divided	1300 (26.25)	110 (8.46)	671 (51.62)	519 (39.92)
Three way divided	566 (11.43)	50 (8.83)	328 (57.95)	188 (33.22)
Undivided road	2015 (40.69)	169 (8.39)	1098 (54.49)	748 (37.12)
Others (e.g., walking street)[a]	1071 (21.63)	76 (7.10)	575 (53.69)	420 (39.22)
State of the road: wet	1848 (37.32)	170 (9.2)	999 (54.06)	679 (36.74)
Speed limit: low (speed limit < 50 kmh)	161 (3.25)	4 (2.48)	81 (50.31)	76 (47.20)
Medium (speed limit = 50 kmh)[a]	3528 (71.24)	191 (5.41)	1915 (54.28)	1422 (40.31)
High (speed limit > 50 kmh)	1263 (25.50)	210 (16.63)	676 (53.52)	377 (29.85)
Land use features				
Residential area	2622 (52.95)	156 (5.95)	1429 (54.5)	1037 (39.55)
Shopping area	845 (17.06)	29 (3.43)	467 (55.27)	349 (41.30)
No building	959 (19.37)	184 (19.19)	484 (50.47)	291 (30.34)
Other (e.g., industrial area)[a]	526 (10.62)	36 (6.84)	292 (55.51)	198 (37.64)
Urban	4178 (84.37)	236 (5.65)	2288 (54.76)	1654 (39.59)
Crash characteristics				
Collision point front (vehicle)	1337 (27)	127 (9.50)	701 (52.43)	509 (38.07)
Accidents at intersections	1518 (30.65)	154 (10.14)	840 (55.34)	524 (34.52)
Accidents at school roadways	228 (4.86)	11 (4.82)	111 (48.68)	106 (46.49)
Unit failed to give duty				
Pedestrian only	417 (8.42)	28 (6.71)	249 (59.71)	140 (33.57)
Driver only	516 (10.42)	17 (3.29)	263 (50.97)	236 (45.74)
Both failed to give duty	507 (10.24)	23 (4.54)	256 (50.49)	228 (44.97)
Neither or difficult to determine[a]	3512 (70.92)	337 (9.6)	1904 (54.21)	1271 (36.19)

This table presents the frequencies (percentage in parentheses) of the variables across each injury category. The percentages in the 'Total column' are calculated for each variable in the whole sample, while the percentages in the injury severity columns are calculated for each outcome within one row (variable).

[a] Refers base outcome in the empirical estimation.

Table A.2
Summary of injury severity studies which employed ordered response framework.

Study	Injury severity representation	Analytical framework employed	Unit of analysis	Categories of explanatory variables considered	Summary findings
Kockelman and Kweon (2002)	Four ordinal levels	Ordered probit	Drivers in single vehicle and two vehicle crashes	• Driver characteristics • Vehicle characteristics • Crash characteristics	• Drivers of passenger cars are safer than pickups and SUV in single vehicle crashes.
Abdel-Aty (2003)	Three ordinal levels	Ordered probit	Drivers in accidents at roadsides, signalized intersection and toll plazas	• Driver characteristics • Environmental factors • Vehicle characteristics • Crash characteristics	• Old drivers, male drivers and those not wearing seatbelt have higher probability of injury.
Srinivasan (2002)	Four ordinal levels	Ordered mixed logit	Drivers in motorized accidents	• Driver characteristics • Vehicle characteristics • Environmental factors • Crash characteristics	• Allowing systematically varying thresholds provides better fit and explanation than the fixed threshold ordered response models.
Wang and Kockelman (2005)	Five ordinal levels	Heterosckedastic ordered logit	Vehicle occupants in motorized accidents	• Driver characteristics • Occupant characteristics • Vehicle characteristics • Crash characteristics • Roadway characteristics	• Older occupants, female and occupants struck by heavy vehicles are more likely to sustain more serious injuries.

(continued on next page)

Table A.2 (*continued*)

Study	Injury severity representation	Analytical framework employed	Unit of analysis	Categories of explanatory variables considered	Summary findings
Pai and Saleh (2007)	Three ordinal levels	Ordered probit	Motorcyclist	• Motorcyclist attributes • Vehicle characteristics • Roadway characteristics • Environmental factors • Crash characteristics	• Accidents at signalized intersection are more severe than accidents at non-signalized intersections.
Eluru and Bhat (2007)	Five ordinal levels	Random coefficient ordered logit	Drivers in all motorized accidents	• Driver characteristics • Vehicle characteristics • Roadway characteristics • Environmental factors • Crash characteristics	• Ignoring the potential impact of unobserved heterogeneity leads to biased parameter estimates and elasticity effects.
Eluru et al. (2008)	Four ordinal levels	Mixed generalized ordered logit	Cyclists and pedestrians	• Non-motorist attributes • Driver attributes • Vehicle characteristics • Roadway characteristics • Environmental factors • Crash characteristics	• A more comprehensive model (MGORL) provided superior performance and reveals that the standard ordered response models could provide inconsistent inferences unless its drawbacks are handled statistically.
Quddus et al. (2010)	Three ordinal levels	Partial proportional odds model	Drivers in accidents on motorways	• Roadway characteristics • Environmental factors • Crash characteristics	• Increased traffic flow reduces the severity of crashes.
Paleti et al. (2010)	Four ordinal levels	Random coefficient ordered logit	Drivers in all motorized accidents	• Driver characteristics • Vehicle characteristics • Roadway characteristics • Environmental factors • Crash characteristics	• Young drivers, drivers who are not wearing seatbelt and under the influence of alcohol are more likely to be aggressive drivers.

Table A.3
Summary of injury severity studies which employed unordered response framework.

Study	Injury severity representation	Analytical framework employed	Unit of analysis	Categories of explanatory variables considered	Summary findings
Shankar et al. (1996)	Four ordinal level	Nested logit	Drivers in accidents at rural freeways	• Driver characteristics • Vehicle characteristics • Roadway characteristics • Environmental factors • Crash characteristics	• The nested logit formulation provided a better fit in capturing the distribution of severity of accidents.
Ulfarsson and Mannering (2004)	Four ordinal level	Multinomial logit	Drivers in accidents in SUV, pickups	• Driver characteristics • Vehicle characteristics • Roadway characteristics • Environmental factors • Crash characteristics	• The effects of many attributes of accidents differ across genders.
Savolainen and Mannering (2007)	Four ordinal level	Nested & multinomial logit	Motorcyclists	• Rider characteristics • Vehicle characteristics • Roadway characteristics • Environmental factors • Crash characteristics	• Increasing age, speeding, darkness and being female increases the likelihood of more serious injuries.
Kim et al. (2007)	Four ordinal levels	Multinomial logit	Bicyclists	• Bicyclist characteristics • Driver characteristics • Vehicle characteristics • Roadway characteristics • Environmental factors • Crash characteristics	• Bicyclists older than 55, bicyclists who are intoxicated and those struck by a speeding vehicle are more likely to sustain fatal injury.
Kim et al. (2008)	Four ordinal levels	Heteroskedastic logit	Pedestrians injury in motor vehicle crashes	• Pedestrian characteristics • Driver characteristics • Vehicle characteristics • Roadway characteristics • Environmental factors • Crash characteristics	• The heteroskedastic logit model performed better than the multinomial logit and pedestrian's age induces heteroskedasticity.
Milton et al. (2008)	Three ordinal levels	Mixed logit	Drivers in accidents on highway segments	• Driver characteristics • Environmental factors • Roadway characteristics	• The mixed logit model which assumed the effects of some attributes of the accident be randomly distributed, provided better fit than the fixed-parameter formulation.

Table A.3 (*continued*)

Study	Injury severity representation	Analytical framework employed	Unit of analysis	Categories of explanatory variables considered	Summary findings
Kim et al. (2010)	Four ordinal levels	Mixed logit	Pedestrian injury in motor vehicle crashes	• Pedestrian characteristics • Driver characteristics • Vehicle characteristics • Roadway characteristics • Environmental factors	• The fit of the heterogeneous mean mixed logit model performs better than the heterosckedastic and nested logit models.
Moore et al. (2011)	Four ordinal levels	Mixed logit	Bicyclists at intersection & non-intersection	• Crash characteristics • Bicyclist characteristics • Driver characteristics • Vehicle characteristics • Roadway characteristics • Environment characteristics	• Effects of some variables on bicyclist injury outcome appears substantially different at intersections and non-intersections.

References

AAA Foundation for Traffic Safety. (2009). *Aggressive driving: Research update*. Washington, DC: AAA Foundation for Traffic Safety, Available at http://www.aaafoundation.org.

Abay, K. A., Paleti, R., & Bhat, C. R. (2012). The joint analysis of injury severity of drivers in two-vehicle crashes accommodating seat belt use endogeneity. Unpublished. Available at http://www.ce.utexas.edu/prof/bhat/ABSTRACTS/Joint_analysis_injury_severity.pdf.

Abdel-Aty, M. (2003). Analysis of driver injury severity levels at multiple locations using ordered probit models. *Journal of Safety Research, 34*(5), 597–603.

Ballesteros, M. F., Dischinger, P. C., & Langenberg, P. (2004). Pedestrian injuries and vehicle type in Maryland, 1995–1999. *Accident Analysis and Prevention, 36*(1), 73–81.

Bhat, C. R. (2001). Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transportation Research Part B, 35*(7), 677–693.

Bhat, C. R. (2003). Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. *Transportation Research Part B, 37*(9), 837–855.

Boes, S., & Winkelmann, R. (2006). Ordered response models. *Allgemeines Statistisches Archiv, 90*(1), 167–181.

Brant, R. (1990). Assessing proportionality in the proportional odds models for ordinal logistics regression. *Biometrics, 46*, 1171–1178.

Castro, M., Paleti, R., & Bhat, C. R. (2012). A latent variable representation of count data models to accommodate spatial and temporal dependence: application to predicting crash frequency at intersections. *Transportation Research Part B, 46*(1), 253–272.

Christoforou, Z., Cohen, S., & Karlaftis, G. M. (2010). Vehicle occupant injury severity on highways: an empirical investigation. *Accident Analysis and Prevention, 42*, 1606–1620.

Eluru, N., & Bhat, C. R. (2007). A joint econometric analysis of seat belt use and crash-related injury severity. *Accident Analysis and Prevention, 39*(5), 1037–1049.

Eluru, N., Bhat, C. R., & Hensher, D. A. (2008). A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. *Accident Analysis and Prevention, 40*(3), 1033–1054.

Elvik, R. (2003). Assessing the validity of road safety evaluation studies by analysing causal chains. *Accident Analysis and Prevention, 35*(5), 741–748.

Elvik, R. (2004). To what extent can theory account for the findings of road safety evaluation studies? *Accident Analysis and Prevention, 36*(5), 841–849.

EuroSafe. (2012). *Child safety country profile*. Denmark: European Child Safety Alliance, Available at http://www.childsafetyeurope.org/reportcards/info/denmark-country-profile.pdf.

Evans, L. (1993). Comments on driver behavior and its role in traffic crashes. *Alcohol, Drugs and Driving, 9*(3–4), 185–195.

Greene, W., & Hensher, D. (2010). *Modeling ordered choices, a primer*. Cambridge: Cambridge University Press.

Holland, C., & Hill, R. (2007). The effect of age, gender and driver status on pedestrians' intentions to cross the road in risky situations. *Accident Analysis and Prevention, 39*(2), 224–237.

International Transport Forum (ITF). (2011). *Pedestrian safety, urban space and health*. Paris. Available at www.internationaltransportforum.org.

Kim, J.-K., Kim, S., Ulfarsson, G. F., & Porrello, L. A. (2007). Bicyclist injury severities in bicycle–motor vehicle accidents. *Accident Analysis and Prevention, 39*(2), 238–251.

Kim, J.-K., Ulfarsson, G. F., Shankar, V. N., & Kim, S. (2008). Age and pedestrian injury severity in motor-vehicle crashes: a heteroskedastic logit analysis. *Accident Analysis and Prevention, 40*(5), 1695–1702.

Kim, J.-K., Ulfarsson, G. F., Shankar, V. N., & Mannering, F. L. (2010). A note on modeling pedestrian-injury severity in motor-vehicle crashes with the mixed logit model. *Accident Analysis and Prevention, 42*(6), 1751–1758.

Kockelman, K. M., & Kweon, Y.-J. (2002). Driver injury severity: an application of ordered probit models. *Accident Analysis and Prevention, 34*(3), 313–321.

Lee, C., & Abdel-Aty, M. (2005). Comprehensive analysis of vehicle–pedestrian crashes at intersections in Florida. *Accident Analysis and Prevention, 37*(4), 775–786.

McFadden, D. (1981). Econometric models of probabilistic choice. In C. Manski, & D. McFadden (Eds.), *Structural analysis of discrete data with econometric applications*. Cambridge, MA: MIT Press.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Applied Econometrics, 15*(5), 447–470.

Milton, J. C., Shankar, V. N., & Mannering, F. L. (2008). Highway accident severities and the mixed logit model: an exploratory empirical analysis. *Accident Analysis and Prevention, 40*(1), 260–266.

Moore, D. N., Schneider, W. H., IV, Savolainen, P. T., & Farzaneh, M. (2011). Mixed logit analysis of bicyclist injury severity resulting from motor vehicle crashes at intersection and non-intersection locations. *Accident Analysis and Prevention, 43*(3), 621–630.

NZTA. (2010). *Economic evaluation manual, Vol. 2*. New Zealand Transport Agency, Available at www.nzta.govt.nz/resources/economic-evaluation-manual/volume-2/docs/eem2-july-2010.pdf.

Pai, C.-W., & Saleh, W. (2007). An analysis of motorcyclist injury severity under various traffic control measures at three-legged junctions in the UK. *Safety Science, 45*(8), 832–847.

Paleti, R., Eluru, N., & Bhat, C. R. (2010). Examining the influence of aggressive driving behavior on driver injury severity in traffic crashes. *Accident Analysis and Prevention, 42*(6), 1839–1854.

Quddus, M. A., Wang, C., & Ison, S. G. (2010). Road traffic congestion and crash severity: econometric analysis using ordered response models. *Journal of Transportation Engineering, 136*(5), 424–435.

Rahul, T. M., & Verma, A. (2012). Economic impact of non-motorized transportation in Indian cities. *Research in Transportation Economics, 1*, 1–13.

Rifaat, S. M., Tay, R., & de Barros, A. (2011). Effect of street pattern on the severity of crashes involving vulnerable road users. *Accident Analysis and Prevention, 43*(1), 276–283.

Savolainen, P., & Mannering, F. (2007). Probabilistic models of motorcyclists' injury severities in single- and multi-vehicle crashes. *Accident Analysis and Prevention, 39*(5), 955–963.

Savolainen, P. T., Mannering, F. L., Lord, D., & Quddus, M. A. (2011). The statistical analysis of highway crash-injury severities: a review and assessment of methodological alternatives. *Accident Analysis and Prevention, 43*(5), 1666–1676.

Shankar, V., Mannering, F., & Barfield, W. (1996). Statistical analysis of accident severity on rural freeways. *Accident Analysis and Prevention, 28*(3), 391–401.

Srinivasan, K. (2002). Injury severity analysis with variable and correlated thresholds: ordered mixed logit formulation. *Transportation Research Record, 1784*(1), 132–141.

Sze, N. N., & Wong, S. C. (2007). Diagnostic analysis of the logistic model for pedestrian injury severity in traffic crashes. *Accident Analysis and Prevention, 39*(6), 1267–1278.

Train, K. (2009). *Discrete choice methods with simulation*. New York, NY: Cambridge University Press.

Ulfarsson, G. F., & Mannering, F. L. (2004). Differences in male and female injury severities in sport-utility vehicle, minivan, pickup and passenger car accidents. *Accident Analysis and Prevention, 36*(2), 135–147.

Wang, X., & Abdel-Aty, M. (2008). Analysis of left-turn crash injury severity by conflicting pattern using partial proportional odds models. *Accident Analysis and Prevention, 40*(5), 1674–1682.

Wang, X., & Kockelman, K. (2005). Use of heteroskcedastic ordered logit model to study severity of occupant injury: distinguishing effects of vehicle weight and type. *Transportation Research Record, 1908*(1), 195–204.

Washington, S. P., Karlaftis, M., & Mannering, F. L. (2011). *Statistical and econometric methods for transportation data analysis* (2nd ed.). Boca Raton, Florida: Chapman & Hall/CRC.

Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *Stata Journal, 6*(1), 58–82.

World Health Organization. (2009a). *Global status report on road safety: Time for action*. Geneva, Switzerland.

World Health Organization. (2009b). *European status report on road safety: Towards safer roads and healthier transport choices*. Copenhagen, Denmark.

Yan, X., Ma, M., Huang, H., Abdel-Aty, M., & Wu, C. (2011). Motor vehicle–bicycle crashes in Beijing: irregular maneuvers, crash patterns, and injury severity. *Accident Analysis and Prevention, 43*(5), 1751–1758.

Ye, F., & Lord, D. (2011). Investigation of effects of underreporting crash data on three commonly used traffic crash severity models. *Transportation Research Record, 2241*(1), 51–58.

Zajac, S. S., & Ivan, J. N. (2003). Factors influencing injury severity of motor vehicle–crossing pedestrian crashes in rural Connecticut. *Accident Analysis and Prevention, 35*(3), 369–379.

Zhu, X., & Srinivasan, S. (2011). A comprehensive analysis of factors influencing the injury-severity of large-truck crashes. *Accident Analysis and Prevention, 43*(1), 49–57.