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A note on accounting for underlying injury-severity states in statistical modeling of injury accident data

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Abstract

This study provides an empirical analysis of the severity outcomes of injury accidents (i.e., accidents that resulted in an injury-involved outcome) by exploring the possibility of two underlying injury-severity states: the minor-injury state and the ordered injury state. The former may reflect the generation mechanism of slight-injury accidents with limited potential to result in more severe injury outcomes, whereas, the latter may represent slight-injury accidents that share similarities with the mechanism of the more severe outcomes, in terms of their occurrence circumstances. To account for the possible presence of these two underlying regimes, a zero-inflated hierarchical ordered probit model with correlated disturbances is estimated using injury-severity data from single-vehicle accidents occurred in Scotland, UK between 2016 and 2017. The results of the empirical analysis provide statistical evidence on the possible presence of underlying states, with the identified effect of traditional driver-, vehicle-, roadway- and accident-specific determinants revealing the nuances and structural differences of such injury-severity states.

Keywords: injury severity; single-vehicle accidents; underlying states; zero-inflated ordered probit; ordered thresholds

1. Introduction

Past research in statistical modeling of accident data has shown that the generation mechanism underpinning the no-injury and injury-involved traffic accidents may differ [1-3]. Typically, no-injury outcomes arise from property-

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damage-only or possible injury accidents [1] that may reflect either low-severity generating conditions (e.g., low-speed collision, vehicle failure) or accident circumstances that could potentially lead to more severe outcomes (e.g., high-speed accidents; run-off-road crashes; collisions with fixed or moving objects on the roadway). Even though the no-injury outcome is the most widely observed in the conventional accident datasets [3], the injury accidents are systematically treated by public agencies, researchers and public community as the most burdensome accidents, with their irreversible effect on public health acting as a driving force towards the implementation of new road safety policies and countermeasures [1]. Injury-specific outcomes typically involve slight injuries (or non-incapacitating injuries), serious injuries (or incapacitating injuries) and fatalities (or fatal injuries). Despite the possible correlation among such ordered injury types, the significant increase in severity from slight injuries to serious or fatal injuries may imply the presence of structural differences in the generation mechanism of various injury accidents types. For example, the possibility of commonly shared variations among the serious and fatal injuries has led to the joint consideration of these two outcomes in recent modeling exercises [4-5]. Despite the likely introduction of aggregation bias, such a consideration may capture similarities in the effect of driver-, vehicle-, or accident-specific covariates on the likelihood of occurrence of serious or fatal injuries.

Such commonly shared variations may not be evident in the generation mechanism of slight injuries. Interestingly, the majority of injury-accident datasets (i.e., datasets including only information for injury-involved accidents) are associated with a preponderance of slight injuries relative to serious or fatal injuries. The latter characteristic may imply the presence of two distinct, yet interrelated regimes underpinning the generation process of the slight injury accidents. The first regime (referred to as minor-injury state) may involve accidents that have resulted either in very minor injuries or possible injuries that have been misclassified as slight injuries, whereas the second regime may involve accidents that could potentially result in serious or fatal injuries, under unfavorable accident-specific circumstances. The latter accidents may share unobserved effects with the serious- and fatal-injury accidents reflecting, thus, the possible presence of a homogeneous generation mechanism (referred to as ordered injury state).

The significant extent of underreporting or misclassification of slight injuries in traditional accident datasets may provide additional evidence with regard to the presence of the underlying states. Specifically, [1, 6-8] mentioned that a significant percentage (ranging from 25% to 75%) of slight-injury crashes may not be reported; this underreporting could be possibly attributed to the minor importance of these accidents as well as to the unwillingness of some drivers to be involved in the post-reporting legal process [1]. On the other side, a considerable portion of the reported slight injuries may, in fact, represent serious injuries, whose severity was underestimated in the police crash reports [9-10].

In this context, ignoring the possible effect of underlying injury-severity states, especially when identifying the determinants of injury-involved accidents, may lead to multiple layers of statistical bias (e.g., bias arising from the incorrect functional form in model estimation as well as aggregation bias) and, ultimately, to invalid parameter estimates. To account for such a masked segmentation of injury accidents, which can be implied by an excessive amount of slight-injury observations, the zero-inflated hierarchical ordered probit with correlated disturbances is employed in this study. The latter allows the identification of factors affecting the injury-severity outcomes through the simultaneous estimation of a binary probit and ordered probit model [3] as well as the identification of factors affecting the ordered probability thresholds through the use of the hierarchical (or generalized) ordered modeling structure [11]. The empirical analysis of injury severities is conducted using a dataset of single-vehicle accidents occurred in Scotland, United Kingdom between 2016 and 2017. Taking into account the generation conditions of the single-vehicle accidents – with the effect of human factors and environmental conditions playing a predominant role in the specific spatial setting – the possible sources of underlying injury-severity states may be particularly influential for this category of accidents.

2. Methodology

Even though the traditional ordered probit approach accommodates the ordinal nature of the injury-severity data **[**12**]**, the assumed homogeneity of the severity function underpinning all the injury outcomes imposes significant limitations [3], especially when an excessive amount of slight-injury accidents is observed. In contrast, the “double-hurdle” nature of the zero-inflated ordered probit approach [13] can accommodate the preponderance of slight-injuries through the incorporation of a splitting function between the minor-injury state and the ordered injury state. This splitting function can take the form of a binary probit model as [2-3, 13]:

$$v_i^* = \mathbf{kD}_i + \varepsilon, \quad v_i = 1 \ (v_i^* > 0) \tag{1}$$

where, v_i^* denotes the latent variable representing the propensity of an injury-involved accident i to belong to the minor injury state (if $v_i^*>0$) or to the ordered injury state (if $v_i^*<0$), v_i is an indicator of the accident-specific injury state, as derived from the value of the latent variable v_i^*, **D** is a vector of exogenous covariates affecting the splitting process, **k** denotes a vector of coefficients corresponding to **D**, and ε represents a standard normally distributed disturbance term.

The determinants of the injury severities of the accidents belonging to the ordered injury state can be identified through an ordered probit model; the latter can be formulated as [12,14-15]:

$$z_i^* = \mathbf{wX}_i + \varepsilon_z,\ z_i^* = y \ \textit{if}\ \mu_y < z_i^* < \mu_{y+1},\ y = 0,1,2. \tag{2}$$

Where, z^* is a latent variable defining the ordered probit model, y represents the observed injury-severity level, **X** denotes a vector of exogenous variables determining the mechanism of the ordered injury state, **w** is a vector of coefficients corresponding to **X**, μ denote the thresholds determining the range of the latent variable for each injury-severity level and ε_Z represents the disturbance term of the ordered probit model, which is assumed to be normally distributed. Under the traditional ordered probit formulation, it is assumed that the threshold parameters are fixed across the accident observations. Such a consideration may conceal possible unobserved variations that could affect the estimation process of the threshold parameters. To that end, the hierarchical ordered probit structure is employed allowing, hence, for the thresholds to be determined as a function of separate covariates [3, 11,15]:

$$\mu_{i,y} = \exp(a_y + \boldsymbol{\delta}\mathbf{C}_i) \tag{3}$$

Where, α is an intercept term, **C** is a vector of threshold-specific covariates and **δ** denotes a vector of parameters specifying the effect of **C** on the ordered thresholds. On the basis of the binary probit and ordered probit model components, two different types of probabilities can be derived. The first type refers to the probability of an accident to result in a slight injury, $P_i(y=0)$, taking into account the explanatory variables determining both injury-severity states [3]:

$$P_i(y=0) = \Phi(\mathbf{k}'\mathbf{D}_i) + \Phi_2(-\mathbf{k}'\mathbf{D}_i, -\mathbf{wX}_i, \rho) \tag{4}$$

where, Φ is the cumulative function of the standard normal distribution and Φ_2 is the cumulative function of the bivariate standard normal distribution. The latter is employed for allowing the unrestricted correlation of the disturbance terms included in the binary probit and ordered probit components, with ρ denoting the corresponding correlation coefficient. The second type of probability, $P_i(y)$ refers to the probability of an accident to result in a serious (y=1) or fatal injury (y=2) conditional on the propensity of the accident to belong in the ordered injury state. This probability can be defined as [3]:

$$P_i(y) = \Phi_2(-\mathbf{k}'\mathbf{D}_i, \mu_{y+1} - \mathbf{wX}_i, \rho) - \Phi_2(-\mathbf{k}'\mathbf{D}_i, \mu_y - \mathbf{wX}_i, \rho),\ \textit{with}\ y = \{1,2\} \tag{5}$$

3. Empirical Setting

For the identification of the determinants of accident injury-severities, we use a dataset consisting of single-vehicle accidents occurred in Scotland, UK. The dataset was drawn from the STATS19 accident database [16] and includes information from police crash reports issued in 2016 and 2017. With regard to the qualitative characteristics of the dataset, four different classes of information were available. The major class of information includes accident- and trip-specific characteristics (e.g., time and location of the accident; trip purpose; injury-severity of the accident; weather and lighting conditions at the time of accident; maneuver of the vehicle at the time of accident; type of collision; vehicle condition immediately after the accident). The other three classes consist of vehicle-specific attributes (type and age of the vehicle), driver's traits (age; gender; type of driver's permanent location) and roadway characteristics (roadway type; roadway surface characteristics; junction presence and type; type of traffic control; presence of pedestrian crossing), respectively.

Even though the vast majority of accidents that occur in UK typically result in a no-injury outcome [9], the STATS19 database [34] includes information only from the police crash reports relating to personal-injury road accidents. To that end, three injury-severity outcomes are reported in the accident dataset: slight injury, serious injury and fatal injury. Compared to the KABCO scale (see [1] for further details), the aforementioned injury-severity levels are similar to the non-incapacitating injury, capacitating injury and fatal injury, respectively. In this study, the observed injury-severity of an accident represents the injury level sustained by the most severely injured individual (driver, passenger, pedestrian or other accident-involved person). The empirical analysis was based on a sample of 5,525 accident observations with a full set of available information. Of the 5,525 accidents, 4,058 (73.45%) resulted in a slight injury, 1332 (24.11%) resulted in a serious injury and the remaining 135 (2.45%) accidents resulted in a fatal injury. Due to an abundance of data elements included in the dataset, Table 1 summarizes the descriptive statistics of the key determinants of injury-severities as identified by the statistical analysis.

Table 1. Descriptive statistics of key variables.

Variable description	**Mean**	**Min**	**Max**
Roadway-specific characteristics			
Roadway type indicator (1 if the accident occurred on a rural single carriageway, 0 otherwise)	36.25%	0	1
Environmental characteristics			
Weather indicator (1 if the accident occurred under fine weather conditions, 0 otherwise)	74.77%	0	1
Driver-specific characteristics			
Age indicator (1 if the driver was younger than 23 years, 0 otherwise)	21.92%	0	1
Vehicle-specific characteristics			
Vehicle age indicator (1 if the vehicle is more than 10 years old, 0 otherwise)	22.50%	0	1
Vehicle type indicator (1 if passenger car, 0 otherwise)	70.86%	0	1
Accident-specific characteristics			
Pedestrian indicator (1 if a pedestrian was involved in the accident, 0 otherwise)	49.63%	0	1
Accident time indicator (1 if the accident occurred between 6.00 am and 9.30 am, 0 otherwise)	14.75%	0	1
Vehicle position indicator (1 if the vehicle did not leave the carriageway, 0 otherwise)	62.24%	0	1
Minor-injury state			
Intersection indicator (1 if the accident occurred on a signalized intersection, 0 otherwise)	7.44%	0	1
Overturned vehicle indicator (1 if the vehicle overturned, 0 otherwise)	5.57%	0	1
Motorcycle indicator (1 if a motorcycle was involved in the accident, 0 otherwise)	6.95%	0	1
Off-the-road object indicator (1 if the vehicle struck a tree off the carriageway, 0 otherwise)	5.39%	0	1
Threshold-specific covariates			
Pavement condition indicator (1 if the pavement was wet, 0 otherwise)	36.92%	0	1
Vehicle maneuver indicator (1 if the vehicle was going ahead without overtaking or turning, 0 otherwise)	49.81%	0	1
Trip purpose indicator (1 if the accident occurred during a work-related trip, 0 otherwise)	20.07%	0	1
Driver's gender indicator (1 if female, 0 otherwise)	28.04%	0	1

4. Analysis and Results

As a significant clustering of slight-injury observations (coded as zero in the employed severity scale) is evident in the accident dataset, the use of a zero-inflated approach for modeling the accident injury severities can account for the possibility of underlying states [17]. Table 2 provides the estimation results of the zero-inflated hierarchical ordered probit model with correlated disturbances[†]. Three separate sets of explanatory variables are identified: (i) factors affecting the probability of an accident to belong in the minor-injury state; (ii) factors affecting the

[†] Note that the maximum likelihood approach was used for the estimation of the zero-inflated ordered probit model [3].

probability of an accident to result in a specific injury outcome conditional on belonging in the ordered injury state; and (iii) variables affecting the ordered probability thresholds.

Table 2 shows that the probability of an accident to result in a slight injury outcome within the context of the minor-injury state is affected by various roadway- and accident-specific characteristics. Specifically, the presence of wet pavement surface at the time of the accident is found to increase the probability of an accident to belong in the minor-injury state. This finding may be picking up the greater extent of driver's alertness [3,18] under inclement weather conditions (e.g., rainfall, fog, high humidity or other types of precipitation); the experience of Scottish drivers on fluctuating environmental conditions resulting in wet pavement conditions for long periods may further enhance their driving alertness. Similarly, slight-injury accidents occurred during work-related trips are more likely to belong in the minor-injury state. The low severity of work-related accidents is consistent with previous research [19] and could be attributed to greater driving cautiousness, due to possible use of business-owned vehicles or due to the high occupancy rate of vehicles used for work-related trips. On the opposite end, vehicles going ahead on the roadway without a deviation of their path – due to a turning or overtaking maneuver – are more likely to belong in the ordered injury state; in such cases, the low complexity of the maneuver-free driving task may enhance the possibility of a risk-taking driving behavior [20]. The variations of risk-taking behavior among the female drivers may also explain the propensity of the latter to be involved in accidents with a potential for major-injury outcomes; note that the indicator variable representing female drivers increases the probability of an accident to belong in the ordered injury state. However, caution should be exercised in the interpretation of this finding because of the highly heterogeneous effect of the gender in driving behavior patterns, as identified by various past studies [e.g., 21-23].

Turning to the determinants of accident injury-severities associated with the ordered injury state, Table 2 shows that an accident occurred on a rural single carriageway is more likely to result in a serious injury or fatality. The relatively high speeds that are typically observed in rural roadways in conjunction with the effect of geometric restrictions of single carriageways (e.g., no division of traffic directions; no medians; limited width of shoulders) on driving behavior constitute favorable conditions for the occurrence of high-severity single-vehicle crashes [24-25]. In similar manner, the presence of favorable weather conditions is also found to increase the probability of more severe injury outcomes, possibly due to the propensity of some drivers to exhibit aggressive behavioral patterns in an effort to compensate for the perceived, weather-driven safety benefits; for further details on the mechanism of risk-compensating behavior, see [26]. With regard to the effect of driver-specific characteristics, Table 2 demonstrates that younger drivers are associated with slight injuries that reflect the generation mechanism of the ordered injury state. Even though this is in line with previous research findings [11], the specific variable may constitute a significant source of unobserved, driver-specific variations [27], whereas its implications on the mechanism of single-vehicle accidents may warrant further investigation. As far as the vehicle-specific characteristics are concerned, passenger cars are found to decrease the probability of more severe injury outcomes (serious injury or fatality); [11] and [23] have also reported similar findings. In contrast, older vehicles (older than 10 years) are found to increase the probability of more severe injury outcomes reflecting, possibly, the propensity of their drivers to exhibit risk-taking behavior. Focusing on the accident-specific contributing factors, pedestrian-vehicle accidents are more likely to result in a serious injury or fatality. This finding is intuitive and may capture the pronounced susceptibility of pedestrians in high-severity outcomes, especially when they are involved in single-vehicle accidents [11]. The opposite effect is observed for accidents occurred during the morning peak hours (6.00 am to 9.30 am), where the prevailing congested conditions, low speeds and drivers' cognitive alertness may constitute favorable circumstances towards the occurrence of conflicts of lower severity, and subsequently, for low-severity accidents. The variable indicating a within-carriageway position of the vehicle at the time of the accident is also found to decrease the probability of a serious injury or fatality. The post-accident path of the vehicle within the roadway may imply the occurrence of a low-severity collision with fixed (e.g., roadway cross-section element; safety barriers; traffic sign) or moving (e.g., animal or moving objects) entities.

The threshold-specific variables determine the threshold distinguishing the value ranges of the latent variable (see Equation 2) corresponding to serious and fatal injuries. Note that, without loss of generality, the first threshold of the ordered probability setting is assumed to be zero (μ_o=0); therefore, only one threshold parameter is computed [12]. Table 2 shows that the occurrence of an accident on a signalized intersection is found to increase the threshold parameter and, hence, to decrease the probability range of fatal injuries in favor of the serious injuries. This finding is intuitive and in line with previous research [15], since the presence of a signalized intersection may enforce lower vehicle speeds and, relatively, reduce the severity of vehicle-to-environment conflicts potentially leading to fatal accidents. Similar effect is also observed for the overturned vehicles. On the contrary, tree-related collisions occurred off the carriageway are found to decrease the threshold parameter leading, thus, to a greater proportion of fatal injuries. The latter is also observed for the motorcycle-involved accidents; the greater exposure of motorcyclists to high-severity collisions may explain their correlation with fatal injuries [28].

To verify the appropriateness of the zero-inflated ordered probit approach relative to the conventional ordered probit approach, which does not address – in principle – the preponderance of slight-injury observations, the Vuong test was conducted [3, 12-13]. The Vuong test statistic (V) is defined by the following equations [3, 12, 29]:

$$V = \frac{\overline{\lambda}\sqrt{N}}{\sigma_\lambda} \tag{6}$$

$$\lambda_i = LN[\, f_1(\theta_i \mid \mathbf{X}_i) \,/\, f_2(\theta_i \mid \mathbf{X}_i)] \tag{7}$$

Where, λ is an observation-specific test value, $f_1(\theta_i|\mathbf{X}_i)$ and $f_2\,(\theta_i|\mathbf{X}_i)$ represent the probability density functions of the conventional ordered probit model (estimated with the same explanatory variables as the zero-inflated model) and the zero-inflated hierarchical ordered probit model, respectively, N is the number of accident observations and σ_λ denotes the standard deviation of the λ values. The calculated value of the Vuong test statistic is -4.65. Considering a 0.95 level of confidence, the absolute value of the test statistic is significantly greater than the corresponding critical value (1.96) warranting, thus, the use of the zero-inflated approach.

The statistical significance of the correlation coefficient provides further evidence on the appropriateness of the zero-inflated approach with correlated disturbances and reflects the influential role of the systematic unobserved variations that are commonly shared between the minor and ordered injury states [3]. The negative sign of the coefficient is intuitive and shows that the unobserved characteristics that have a negative impact on the probability of an accident to belong in the minor-injury state may simultaneously favour the probability of a severe injury outcome within the ordered injury state.

Table 2. Estimation results of the zero-inflated hierarchical ordered probit model with correlated disturbances.

Variable description	**Coefficient**	***t*-stat**
Constant	0.463	2.23
Roadway-specific characteristics		
Roadway type indicator (1 if the accident occurred on a rural single carriageway, 0 otherwise)	0.227	3.47
Environmental characteristics		
Weather indicator (1 if the accident occurred under fine weather conditions, 0 otherwise)	0.296	4.27
Driver-specific characteristics		
Age indicator (1 if the driver was younger than 23 years, 0 otherwise)	-0.171	-2.89
Vehicle-specific characteristics		
Vehicle age indicator (1 if the vehicle is more than 10 years old, 0 otherwise)	0.164	2.68
Vehicle type indicator (1 if passenger car, 0 otherwise)	-0.484	-5.03
Accident-specific characteristics		
Pedestrian indicator (1 if a pedestrian was involved in the accident, 0 otherwise)	0.365	4.13
Accident time indicator (1 if the accident occurred between 6.00 am and 9.30 am, 0 otherwise)	-0.231	-3.08
Vehicle position indicator (1 if the vehicle did not leave the carriageway during the accident, 0 otherwise)	-0.149	-2.10
Threshold-specific explanatory variables		
Intersection indicator (1 if the accident occurred on a signalized intersection, 0 otherwise)	0.206	3.19
Overturned vehicle indicator (1 if the vehicle overturned, 0 otherwise)	0.172	3.18
Motorcycle indicator (1 if a motorcycle was involved in the accident, 0 otherwise)	-0.267	-3.67
Off-the-road object indicator (1 if the vehicle struck a tree off the carriageway, 0 otherwise)	-0.085	-1.69
Minor-injury state		
Pavement condition indicator (1 if the pavement was wet, 0 otherwise)	0.183	1.69
Vehicle maneuver indicator (1 if the vehicle was going ahead without overtaking or turning, 0 otherwise)	-0.229	-2.20
Trip purpose indicator (1 if the accident occurred during a work-related trip, 0 otherwise)	0.282	4.05
Driver's gender indicator (1 if female, 0 otherwise)	-0.212	-2.33
Intercept for μ_1	0.372	1.95
Correlation coefficient of disturbance terms	-0.663	-2.59
Number of observations	5,525	
Restricted log-likelihood, $LL(0)$	-3648.37	
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-3544.69	

5. Summary and Conclusions

Even though the impact of underlying states stemming from the no-injury mechanism has been recently accounted for in accident research [2-3], the possibility of latent injury-severity states underpinning the mechanism of injury accidents has not been previously explored. This study investigates the possible presence of two underpinning regimes of slight injuries that may induce variations in the effect of the injury-severity determinants. The excessive number of slight-injury observations in conjunction with the impact of underreporting or misclassification of slight injury outcomes in single-vehicle accidents may further substantiate the underlying presence of injury-states in conventional accident datasets. To address this possibility and identify the influential factors of accident injury severities, a zero-inflated hierarchical ordered probit model with correlated disturbances was estimated using single-vehicle accident data from Scottish motorways and carriageways throughout 2016 and 2017. Apart from the underlying injury-severity states, the employed modeling approach addresses – to some extent – threshold heterogeneity, through the use of the hierarchical ordered structure, and accounts for possible correlation of the disturbance terms included in the model components.

The model estimation results show that driving on wet pavement surface and for work-related trips may impose accident-specific circumstances leading to slight injuries with limited potential burden. On the contrary, pedestrian-involved accidents, accidents involving old vehicles, accidents occurred in rural single carriageways and under fine weather conditions may share similarities with the severity mechanism of the ordered injury state resulting, thus, in more severe injury outcomes. However, the findings of this study may be subject to the effect of systematic underlying variations between the minor and ordered injury state; these variations were accounted for through the consideration of unrestricted correlation of the disturbance terms, which was found to have a statistically significant effect on the injury-severity determinants. Such unobserved variations may be evident not only in the disturbance terms of the model components of the zero-inflated ordered model, but also within each injury state as well as at an observation-specific level [30-32]. Thus, the outcomes of this study can form the basis for future work on the identification of additional sources (e.g., human, spatial, or temporal) of unobserved heterogeneity [27], which, in conjunction with the underlying injury-severity states, may affect the robustness and forecasting accuracy of the accident injury-severity models. With the rise of emerging technologies [33], the importance of such models for the decomposition of vehicle-to-vehicle and vehicle-to-infrastructure heterogeneity is more imminent than ever [35].

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