The joint effect of weather and lighting conditions on injury severities of single-vehicle accidents

by

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ABSTRACT

This study seeks to identify and analyze variations in the effect of contributing factors on injury severities of single-vehicle accidents across various lighting and weather conditions. To that end, injury-severity data from single-vehicle, injury accidents occurred in Scotland, United Kingdom in 2016 and 2017 are statistically modeled. Upon the conduct of likelihood ratio tests, separate models of accident injury severities are estimated for various combinations of weather and lighting conditions taking also into account the presence and operation of roadside lighting infrastructure. To account for the possibility of unobserved regimes underpinning the injury-severity mechanism, the zero-inflated hierarchical ordered probit approach with correlated disturbances is employed. The approach also relaxes the fixed threshold restriction of the traditional ordered probability models and captures systematic unobserved variations between the underlying regimes. The model estimation results show that a wide range of accident, vehicle, driver, trip and location characteristics have varying impacts on injury severities when different weather and lighting conditions are jointly considered. Even though several factors are identified to have overall consistent effects on injury severities, the simultaneous impact of unfavorable weather and lighting conditions is found to introduce significant variations, especially in the effect of vehicle- and driver-specific characteristics. The findings of this study can be leveraged in vehicle-to-infrastructure or in-vehicle communication technologies that can assist drivers in their responses against hazardous environmental conditions.

KEYWORDS

Injury severity; Zero-inflated ordered probit; Weather; Lighting conditions; Single vehicle accidents; Scotland

INTRODUCTION

In modern accident research, lighting characteristics have long been recognized as a major class of environmental factors with critical effect on the likelihood of accident occurrence as well as on the resulting injury severity of the accidents. The impact of such characteristics on the accident generation mechanism is primarily determined by the ambient lighting conditions (e.g., daylight or darkness) at the time of the accident. The presence and operation of roadway lighting systems constitutes an infrastructure-specific dimension, which can effectively mitigate the unfavorable effects of natural illumination. The degree of driver's visibility and perception significantly varies when driving in dark conditions with street lights in operation and when driving in dark conditions with no street lights at all or with limited street lighting. The variations of lighting conditions interact with drivers' behavioral and cognitive responses, traffic conditions, and vehicle-related safety and operational features in determining the driving style and so the insurgence of risky behaviour. In general, driving under dark conditions may result in impairments on drivers' hazard perception, visual performance and reaction time (Plainis and Murray, 2002; Jägerbrand and Sjöbergh, 2016; Fylan et al., 2018), whereas the ample visibility observed during daylight may result in risk-compensating adjustments of driving behavior (Jägerbrand and Sjöbergh, 2016). Despite the restricted visibility induced by dark conditions, the low traffic patterns at night time in conjunction with the inherent characteristics of the drivers traveling during such times may lead to risk-taking driving patterns such as speeding or traffic light violations (de Bellis et al., 2018; Jensupakarn and Kanitpong, 2018).

The effect of lighting characteristics on driving behavior depends on other environmental factors, in particular weather conditions. Adverse weather conditions decrease the available visibility to the driver and distort driving-related cognitive functions, thus increasing the probability of driving errors and hazardous driving actions (Peng et al., 2018; Almawmasi and

Mannering, 2019). These errors are far more evident when driving under the joint impact of inclement weather and restricted lighting conditions, with the occurrence of high-severity accidents being a likely outcome of such driving errors (Wali et al., 2018).

A number of studies have investigated the effect of lighting or weather conditions on accident injury severities (Abdel-Aty, 2003; Golob and Recker, 2003; Wanvik, 2009; Naik et al., 2016; Shaheed et al., 2016; Uddin and Huynh, 2017; Ariannezhad and Wu, 2018; Li et al., 2018). Quite a few of these studies analyzed the effect of weather or lighting characteristics through the inclusion of indicator variables capturing the individual or joint effects of such environmental conditions. Acknowledging the aggregate nature of indicator variables and their limitations in capturing human factor-driven variations (Islam and Mannering, 2006; Morgan and Mannering, 2011), a growing stream of recent studies (to name a few, Behnood et al., 2014; Almawmasi and Mannering, 2019; Behnood and Mannering, 2019; Guo et al., 2020) account for variations in the determinants of accident injury-severities by estimating separate statistical models per homogeneous groups of accident population or driving population with distinct characteristics. Focusing on the effect of lighting characteristics, Anarkooli and Hosseinlou (2016), Uddin and Huynh (2017) and Islam and Burton (2019) estimated separate models of injury severities for accidents occurred under various lighting conditions (e.g., daylight, dark conditions or dark conditions with street lights in operation). Following a similar approach, but with special focus on the impact of weather conditions, a set of previous studies (Shaheed et al., 2016; Hao and Daniel, 2016; Naik et al., 2016; Hao et al., 2017) developed separate injury-severity models by considering groups of accidents occurred under various weather conditions (e.g., rain, snow, fog and so on).

Even though the individual impacts of lighting or weather characteristics on accident injury-severities have been extensively studied, the mechanism underpinning the simultaneous effect of both environmental factors has not been fully understood to date. In this context, Ariannezhad and Wu (2018) have recently investigated the injury severities of accidents occurred during a specific period of the year with unique weather characteristics (monsoon period in Arizona, US) considering combinations of lighting (day-time versus night-time) and weather (rainfall versus clear) characteristics. The results of the statistical analysis showed that the interactions of weather and lighting conditions at the time of the accident induce significant variations in the effect of the influential factors on accident injury-severities.

This study aims at investigating the interactive effect of weather and lighting characteristics on accident injury severities at a more disaggregate level. In this context, the analysis is focused on single-vehicle accidents that have resulted in an injury or fatal outcome. To control for various interactions of the weather and lighting characteristics, which may not be limited to the ambient conditions of the physical environment, three dimensions are jointly considered for the analysis of accident injury severities: (i) natural lighting conditions at the time of the accident; (ii) presence and operation of lighting infrastructure at the time of the accident; and (iii) weather conditions at the time of the accident. On the basis of these dimensions, this study seeks to identify the specific sets of determinants of accident injury-severities for various interactions of weather and lighting characteristics as well as the variations in the effect of injury-severity determinants due to such interactions.

In single-vehicle accidents, human error typically constitutes one of the major factors leading to accident occurrence (Alnawmasi and Mannering, 2019). Given that the joint consideration can control for the effect of various weather and lighting characteristics on accident injury severities, the identified determinants are primarily subject to variations arising from human factor elements as well as from unobserved, accident-specific circumstances. The latter factors may have a particular effect on the generation mechanism of slight-injury accidents, which may interact with the underlying sources of these accidents. Specifically, Fountas and Rye (2019) identified two regimes of slight-injury accidents: a portion of slight-injury outcomes may reflect very minor accident circumstances with limited potential to result in more severe injuries, whereas other slight-injury accidents may have a potential for greater injury-severity risk under more unfavorable accident circumstances. As such, to capture the effect of injury-severity determinants to a more disaggregate extent while accounting for the possible presence of underlying injury-severity states, the zero-inflated hierarchical ordered probit model with correlated disturbances is employed for the statistical analysis of the injury-severity data. Therefore, the employed methodological framework incorporates two top-down and interrelated layers of accident segmentation in the statistical analysis of injury data: (i) through the identification of observed sub-groups of accident population corresponding to various weather and lighting combinations; and (ii) through the identification of unobserved regimes of accidents within each of the aforementioned sub-groups of accident population.

EMPIRICAL SETTING

To identify the determinants of accident injury severities under different weather and lighting conditions, accident data from Scotland, UK were used. The specific area is associated with significant weather and lighting fluctuations observed across short time intervals; such fluctuations are expected to have a considerable effect on drivers' behavioral responses, thus increasing the likelihood of hazardous driving incidents (Stradling, 2007).

Specifically, information about single-vehicle accidents occurred in various roadway types of Scotland, UK between 2016 and 2017 was drawn from the STATS19 dataset. The latter is a publicly available database compiling various accident-related characteristics, as derived from standardized police crash reports (Department for Transport, 2018). A limitation of the STATS19 dataset is that includes information only for injury-involved accidents (Imprialou and Quddus, 2019), whereas the accidents resulting in a no-injury outcome are not reported. Following the STATS19 injury classification, three injury-severity outcomes are considered in this study: slight injury, serious injury and fatal injury[1]. Apart from the injury-severity outcomes, the accident dataset encompasses various layers of accident-related information. More specifically, the latter consists of: (i) accident characteristics (such as accident date and location, accident type, vehicle action before and after the accident, point of impact during the accident); (ii) drivers' and casualties' attributes (age, gender, type of household location); (iii) roadway and geometric design characteristics (roadway type and class, roadway surface conditions at the time of the accident, presence, type and location of intersection; presence and type of pedestrian crossing); (iv) vehicle characteristics (vehicle age and type, engine capacity, vehicle condition immediately after the accident); and (v) environmental factors (weather and lighting conditions).

The dataset used for model estimation includes 5,525 observations of single-vehicle accidents. With respect to their injury-severity outcomes, slight injuries were reported in 73.45% of the accidents, serious injuries were in 24.10% of cases, whereas the remaining 2.45% of the records were associated with a fatal injury outcome[2]. As shown in Figure 1, which provides the distribution of injury outcomes for various combinations of weather and lighting conditions, the accident observations show a consistent clustering at the slight-injury level. This distributional characteristic of accident observations may imply the existence of underlying injury-severity regimes affecting the accident generation mechanism.

The accident dataset used for the statistical analysis includes a plethora of potential explanatory variables, as such, Table 1 provides the descriptive statistics of the explanatory variables that were identified as statistically significant factors of accident injury severities in the estimated models.

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[1] Note that the reported injury-severity outcomes are counterparts of the following outcomes included in the KABCO scale (Savolainen et al., 2011): non-incapacitating injury, incapacitating injury and fatal injury.

[2] In line with previous injury-severity analyses (Anastasopoulos and Mannering, 2011; Fountas and Anastasopoulos, 2017; Fountas and Anastasopoulos, 2018a; Fountas and Anastasopoulos 2018b; Fountas and Rye, 2019; Behnood and Mannering, 2019), the injury-severity outcome of an accident is drawn from the vehicle occupant(s) observed to sustain the most severe injury in the accident.

INSERT FIGURE 1

INSERT TABLE 1

METHODOLOGICAL APPROACH

From a methodological perspective, a number of studies focusing on the impact of lighting or weather characteristics have adopted the ordered probit/logit framework for the statistical analysis of the accident injury severities (Russo et al., 2014; Naik et al., 2016; Anarkooli and Hosseinlou, 2016; Ghasemzadeh and Ahmed, 2018; Osman et al., 2018; Bhowmik et al., 2019). Although the conventional ordered probability models can tackle the inherent ordering of the injury-severity data, they exhibit limitations in accommodating underlying variations that may be present in datasets exhibit clustering of accidents with low-severity outcomes (Jiang et al., 2013; Fountas and Anastasopoulos, 2018; Fountas and Rye, 2019). These limitations primarily arise from the consideration of a homogeneous source related to the generation process of the injury–severity outcomes. In datasets consisting only of accidents that resulted in an injury outcome, the observations of low-severity injuries are typically preponderant. Such a preponderance may imply that the mechanism underpinning the outcomes of the injury accidents is not uniform and there may be underlying characteristics interacting with latent sub-groups of this accident type.

Unlike the conventional ordered probability models, the zero-inflated ordered probit models can account for the aforementioned limitation, as their "double-hurdle" structure enables the consideration of two underlying states for low-severity accidents. Focusing on the injury accidents, the first state, namely the minor-injury state, may be formed by very minor accidents with low energy dissipation leading to minor injuries or outcomes of even lower severity (e.g., possible injuries) that have been reported as slight injuries (Fountas and Rye, 2019). The second state, the ordered injury state concerns slight-injury accidents, which – under the impact of more adverse accident circumstances – could lead to more severe injuries. The ordered injury state also accounts for serious or fatal injuries, with their underlying generation mechanism sharing a lot of similarities with the aforementioned group of slight-injury accidents (Fountas and Rye, 2019).

The zero-inflated ordered probit model consists of a binary probit component and an ordered probit component, which are simultaneously estimated through a maximum likelihood estimation approach. The binary probit component serves as a splitting function between the injury-severity states, with its explanatory variables determining whether an accident is associated with the minor-injury state or not. The binary probit component can be defined as (Harris and Zhao, 2007; Fountas and Anastasopoulos, 2018; Fountas and Rye, 2019):

$$\omega_i^* = \boldsymbol{\lambda}\boldsymbol{\Gamma}_i + w \quad (1)$$

and

$$\omega_i = \begin{cases} 0, & if \ \ \omega_i^* \leq 0 \\ 1, & if \ \ \omega_i^* > 0 \end{cases} \quad (2)$$

where, ω_i^* is a latent variable reflecting the propensity of an accident *i* to be associated with the minor-injury state, ω_i is derived from the latent variable ω_i^* and indicates whether the accident *i* belongs to the minor-injury state (ω_i=1) or not (ω_i=0), $\boldsymbol{\Gamma}$ represents a vector of independent variables, λ denotes a vector of estimable parameters, and w denotes a disturbance term following the standard normal distribution.

To identify the factors affecting the injury severity outcome of the accidents belonging to the ordered injury state (i.e., ω_i=0 according to Equation 2), the ordered probit component is defined as (Washington et al., 2011; Fountas et al., 2018a; Fountas et al., 2018b; Pantangi et al., 2020):

$$y_i^* = \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i, \ \ y_i^* = k \ if \ \mu_k < y_i^* < \mu_{k+1}, \ \ \forall i \,|\, \omega_i = 0 \quad (3)$$

Where, y_i^* represents a latent variable defining the injury severity outcome k of the accident observation i, with the severity ranging between slight injury (k=0), serious injury (k=1) and fatal injury (k=2), **X** denotes a vector of independent variables affecting the injury-severity outcome, **β** denotes a vector of estimable parameters corresponding to **X**, μ represent the ordered thresholds defining the probability range for each injury-severity outcome and ε_i is a normally distributed disturbance term.

An inherent assumption of the traditional ordered probit model is that the threshold parameters are specified as constant values. Given that the threshold parameters may be affected by unobserved heterogeneity (Eluru et al., 2008; Fountas and Anastasopoulos, 2017; Fountas and Anastasopoulos, 2018), we employ a more flexible model formulation by defining these parameters as a function of exogenous variables. To that end, a hierarchical ordered probit model is specified as (Greene, 2016; Fountas and Anastasopoulos, 2018; Fountas and Rye, 2019)[3]:

$$\mu_{i,y} = \exp(c_k + \boldsymbol{v}\mathbf{Z}_i) \tag{4}$$

where, c is a constant, **Z** is a vector of explanatory variables defining the ordered thresholds and **v** denotes a vector of estimable parameters corresponding to **Z**. Note that, without loss of generality, the first threshold (μ_0) of the ordered process is defined as zero. In this case, K-2 thresholds will be estimated (Washington et al., 2011), where K is the number of injury-severity outcomes considered in the statistical analysis.

To identify the magnitude of the effect of the injury-severity determinants, marginal effects are also computed. Marginal effects show how much the probability of an accident to result in a specific injury-severity outcome will be affected by a unit change in the value of an independent variable and can be defined as (Harris and Zhao, 2007):

[3] The hierarchical ordered probit model has the same formulation as the generalized ordered response models: in both cases thresholds can vary as a function of exogenous variables (see also Eluru et al., 2008; Yasmin et al., 2015; Bhowmik et al., 2019).

$$ME_{\mathbf{X}} = \frac{\partial P(k)_i}{\partial \mathbf{X}} = \frac{\partial[\Phi_2(-\lambda\boldsymbol{\Gamma}_i, \mu_k - \boldsymbol{\beta}\mathbf{X}_i, \rho) - \Phi_2(-\lambda\boldsymbol{\Gamma}_i, \mu_{k-1} - \boldsymbol{\beta}\mathbf{X}_i, \rho)]}{\partial \mathbf{X}} \quad (5)$$

where, $P(k)_i$ is the probability of an accident i to result in a specific injury-severity outcome k, Φ_2 represents the cumulative bivariate standard normal distribution, and ρ is the coefficient capturing the correlation of disturbance terms between the binary probit and ordered probit components. Unlike previous zero-inflated ordered probit applications, herein we employ a bivariate standard normal distribution for the disturbance terms, which enables the latter to be freely correlated (Eker et al., 2019; Eker et al., 2020). This is important because the correlation of disturbance terms may capture unobserved variations commonly shared between the minor-injury state and the ordered injury state (Fountas and Anastasopoulos, 2018).

ANALYSIS AND RESULTS

To statistically identify whether the factors affecting the accident injury severities vary across different weather and lighting conditions, a likelihood ratio test was conducted. This test can demonstrate whether the parameters of a statistical model based on a comprehensive accident dataset are transferable to various sub-groups of the accident population, which exhibit variations among each other with respect to various qualitative characteristics (Washington et al., 2011; Behnood et al., 2014; Fountas et al., 2019). To capture possible variations in the determinants of injury severities of single-vehicle accidents, 6 combinations of weather and lighting conditions were considered, by additionally taking into account variations in the presence and operation of the roadway lighting infrastructure. These combinations are: (i) daylight and fine weather conditions; (ii) daylight and poor weather conditions; (iii) darkness and fine weather conditions on lighted roadways; (iv) darkness and poor weather conditions on lighted roadways; (v) darkness and fine weather conditions on unlighted roadways; and (vi) darkness and poor weather conditions on unlighted roadways. According to the description provided by the STATS19 reporting system, fine weather reflects weather conditions that do not impede driving performance, whereas poor weather refers to adverse weather conditions with anticipated impact on driving performance, such as rainfall, snowfall, fog or high winds. With regard to the lighting infrastructure, unlighted roadways refer either to roadways without lighting infrastructure or to roadways with lighting infrastructure not being in operation at the time of the accident. The likelihood ratio test statistic can be formulated as (Washington et al., 2011):

$$X^2 = -2[LL(\boldsymbol{\beta}_{\mathrm{F}}) - LL(\boldsymbol{\beta}_{\mathrm{DF}}) - LL(\boldsymbol{\beta}_{\mathrm{DP}}) - LL(\boldsymbol{\beta}_{\mathrm{DRLTF}}) - LL(\boldsymbol{\beta}_{\mathrm{DRLTP}}) - LL(\boldsymbol{\beta}_{\mathrm{DRNLF}}) - LL(\boldsymbol{\beta}_{\mathrm{DRNLP}})] \quad (6)$$

where $LL(\boldsymbol{\beta}_{\mathrm{F}})$ is the log-likelihood at convergence of the model estimated using the full dataset (full model), whereas the $LL(\boldsymbol{\beta}_{\mathrm{DF}})$, $LL(\boldsymbol{\beta}_{\mathrm{DP}})$, $LL(\boldsymbol{\beta}_{\mathrm{DRLTF}})$, $LL(\boldsymbol{\beta}_{\mathrm{DRLTP}})$, $LL(\boldsymbol{\beta}_{\mathrm{DRNLF}})$ and $LL(\boldsymbol{\beta}_{\mathrm{DRNLP}})$ denote the log-likelihood at convergence of the models estimated using subsets corresponding to weather and lighting combinations (subset data models).[4] The likelihood ratio test is chi-square distributed, with its degrees of freedom being determined by the difference between the summation of parameters included in the subset data models and the number of parameters in the full model. For the calculation of the test statistic, the zero-inflated hierarchical ordered probit model with correlated disturbances estimated by Fountas and Rye (2019) served as the full model[5]. In the specific study, the same dataset (including all the single-vehicle accidents occurred in Scotland in 2016 and 2017) was used for the statistical analysis of accident injury-severities. The calculated test statistic is equal to 182.75 and, considering 80 degrees of freedom, the critical chi-squared value is equal to 112.33 at a 99% level of confidence. These results show that the factors affecting the accident injury severities may vary across different combinations of weather and lighting conditions with greater than

[4] For the definitions of the notations included as subscripts of the $LL(\boldsymbol{\beta})$s, see Table 1.

[5] In addition to the model estimated by Fountas and Rye (2019), several other model specifications were tested through likelihood ratio tests to identify whether the determinants of accident injury severities are transferable across different weather and lighting conditions. These specifications also included interactive variables that capture interactions of vehicle, roadway and driver characteristics with weather and lighting conditions. In all cases, the results of the likelihood ratio tests showed that the estimated models are non-transferable across different combinations of weather and lighting conditions, thus substantiating the estimation of separate models.

99% level of confidence. Thus, the estimation of separate models for the aforementioned combinations is statistically warranted.

Tables 2-4 present the model estimation results of the injury-severity models along with their corresponding marginal effects. Note that numerous variable combinations have been extensively investigated as potential explanatory variables in the presented model specifications. Overall, significant variations have been identified in the effect of the injury-severity determinants across the considered sub-groups of the accident population, in terms of statistical significance, magnitude and sign. To highlight such differences, the model estimation results are discussed per category of contributing factors.

INSERT TABLE 2

INSERT TABLE 3

INSERT TABLE 4

Accident-specific contributing factors

Various accident-specific factors are found to affect the minor and ordered injury severity states among the considered weather and lighting combinations. For example, under daylight and poor weather conditions, accidents involving skidding vehicles are more likely to result in slight injuries (by 0.0176 as shown by the corresponding marginal effect in Table 2) and less likely to result in serious and fatal injuries (by -0.0175 and -0.0001, respectively, as shown by the marginal effects in Table 2). A similar effect is observed in accidents occurred on unlighted roadways under dark and fine weather conditions, when the skidding is accompanied by overturning of the vehicle. Skidding vehicles are also found to increase the threshold between the serious and fatal injuries in the model reflecting daylight and fine weather conditions. Such an increase entails a higher probability of a serious injury outcome relative to a fatal injury outcome (see also the discussion provided in Fountas and

Anastasopoulos, 2017 regarding the implications of threshold variations on the probabilities of high-severity outcomes). Skidding incidents typically occur on a slippery pavement surface, which is perceived by drivers as a roadway hazard that can lead to loss of steering control. As in similar cases of evident roadway hazards, drivers may compensate for the high accident risk by exhibiting greater driving caution (for a more detailed discussion on the implications of risk perception in driving task, see also Mannering and Bhat, 2014 and Mannering et al., 2020).

Accidents involving collisions with trees are consistently found to increase the likelihood of serious or fatal injuries in the models for daylight and fine weather, daylight and poor weather as well as for darkness and fine weather on unlighted roadways. Specifically, tree-related collisions are found to have the strongest effect on serious injuries under daylight and poor weather (the corresponding marginal effect is 0.1355) and the strongest effect on fatal injuries under daylight and fine weather (the corresponding marginal effect is 0.1107). Given the high amount of energy dissipated in tree-related accidents, their correlation with high-severity outcomes is intuitive and in line with several previous studies (e.g., Holdridge et al., 2005; Van Treese et al., 2019). Similarly, in accidents occurred under daylight and fine weather conditions, collisions with roadside curbs are found to increase the threshold between the serious and fatal injuries, thus leading to a higher likelihood of fatal injuries. This finding may reflect accidents occurred on high-speed roadways, where the curb-related accidents are typically associated with more severe injuries (Plaxico, 2005). In accidents observed under such favorable environmental conditions, the curb-related accidents may imply more dangerous collisions with the roadside infrastructure increasing the probability of fatal injuries.

The pedestrian involvement in the accident is repeatedly found to increase the likelihood of severe injury outcomes (serious and fatal injury) in all models but those reflecting darkness and fine or poor weather on lighted roadways. Also, this result is in line with a stream of previous studies (e.g., Behnood and Mannering, 2015; Fountas and Anastasopoulos, 2017), which show that the injury-severity mechanism of the accidents involving pedestrians may not significantly vary across different environmental conditions. It should be noted that the most pronounced effect of the pedestrian involvement indicator on serious and fatal injuries is identified in the model reflecting darkness and poor weather on unlighted roadways (the corresponding marginal effects are 0.1 and 0.2852, respectively), whereas the least pronounced effect is observed in the model reflecting daylight and poor weather (the corresponding marginal effects are 0.0214 and 0.0005, respectively). Even though better lighting conditions can reduce the risk for pedestrian-involved accidents, their effect in the resulting injury severity may not be as critical as the vulnerability of pedestrians in such high-impact collisions.

In contrast, vehicles that ran off the roadway are associated with varying effects on injury severity outcomes across different lighting and weather conditions. In daylight and fine weather conditions, the accidents involving run-off-the-road vehicles are more likely to result in serious or fatal injuries (by 0.0092 and 0.0346, respectively), as shown by the marginal effects in Table 2; the difference in the magnitude of marginal effects for serious and fatal outcomes underscores the significant correlation of run-off-the-road vehicles with fatal injuries under normal driving conditions. When the same type of accidents occurs at lighted roadways at night, their injury severity is found to be affected by the prevailing weather conditions. Specifically, under fine weather, these accidents are more likely to result in slight injuries, whereas in poor weather, they are found to be associated with the minor-injury state, hence, with accidents of very low severity. Overall, the identified disparities in the effect of the run-off-the-road-vehicles on injury-severities show that the combination of unfavorable lighting and weather conditions may induce risk-compensating elements in driving behavior resulting in less severe injuries.

Vehicles reversing at the time of the accident are found to favor slight injury accidents under daylight regardless of the weather conditions. The strongest – in magnitude – impact of the reversing maneuver is observed under fine weather conditions where the likelihood of a slight injury increases by 0.0571, whereas, under poor weather conditions, the same likelihood increases by 0.0151.

Roadway-specific contributing factors

Speed limit was identified to affect the likelihood of minor-injury state in most injury-severity models. Higher speed limits are found to decrease the likelihood of minor-injury state (increasing, hence, the likelihood of ordered injury state) for accidents occurred in daylight and fine weather. Similarly, accidents on lighted and unlighted roadways with speed limit greater than 30 mph under dark and fine weather conditions are more likely to belong to the ordered injury state. The same variable is also found to increase the threshold between serious and fatal injuries in the model reflecting daylight and poor weather implicating, thus, an increase in the likelihood of fatal injuries. The most pronounced effect of speed limit is identified under darkness and fine weather on unlighted roadways, where the likelihood of serious and fatal injuries increases by 0.1381 and 0.0239, respectively. Overall, accidents at high-speed roadways are consistently found to be correlated with more severe injuries, verifying the well-established relationship between speed and injury risk (Richards, 2010).

With regard to the roadway type, Table 2 shows that accidents on dual carriageways in daylight and poor weather are more likely to result in more severe injuries. The opposite effect is observed in unlighted dual carriageways located in urban areas; in dark and fine weather conditions, the likelihood of serious and fatal injuries is found to decrease by -0.1298 and -0.0262, respectively (see Table 4). The latter finding may capture the joint effect of urban traffic patterns and higher driver's alertness in response to dark conditions. Such a combination may decrease the running speed, and subsequently, the risk for severe accidents. Accidents in rural single carriageways are found to be associated with slight injuries in the models representing darkness and inclement weather conditions on lighted and unlighted roadways.

However, the effect of rural single carriageways is identified to be stronger under dark and poor weather conditions on unlighted roadways, as the likelihood of the slight injury outcome increases by 0.1378; the corresponding effect is found to be subtler under dark and poor weather conditions on lighted roadways, as the same likelihood increases by 0.0549. The difference in the magnitude of the marginal effects may indicate that drivers are more cautious in the absence or non-operation of roadway lighting infrastructure. It should be noted that single carriageways are undivided highways with typically lower speed limits compared to the dual carriageways where the opposing directions are divided through medians. Even though dual carriageways are considered safer than the single carriageways (Gray, 2008), the combined effect of inclement weather and dark conditions may encourage drivers to exercise greater driving caution as a kind of compensation for the lack of separation and the closer distances kept between the opposing directions in single carriageways.

Accidents on dry pavements in daylight and poor weather as well as accidents under darkness and fine weather conditions on lighted roadways are associated with the minor-injury state. The effect of dry pavements on the likelihood of a slight injury is stronger in magnitude under darkness with fine weather on lighted roadways rather than in daylight and poor weather (the corresponding marginal effect are 0.0377 and 0.015 respectively). In contrast, on unlighted roadways at night with fine weather conditions, the presence of a dry pavement is correlated with the ordered injury state, i.e. it is linked to more severe outcomes.

Driver-specific contributing factors

Driver’s age was identified to have a multifaceted effect on accident injury severities. Focusing on accidents occurred in daylight, the involvement of novice and very young drivers in an accident is found to increase the probability of slight injuries either related to the minor-injury state (as in the model for daylight and poor weather) or to the ordered injury state (as in the model for daylight and fine weather). However, the presence of dark conditions seems to increase the propensity of young drivers to be involved in accidents with severe injuries. Table 3 shows that the lower the age of the driver, the higher the probability of a more severe injury outcome under darkness and fine weather on lighted roadways. When consideration is given to the same weather conditions but with focus on unlighted roadways, relatively young, yet possibly experienced drivers (between 23 and 37 years old) are found to be more vulnerable to serious or fatal injuries. These findings possibly capture the behavioral patterns of "over-confident" drivers, who are aware of their experience but, due to their age, may be more prone to risk-taking maneuvers. Such maneuvers in conjunction with the restricted visibility observed under darkness, can result in high-impact collisions, and hence, in higher injury severities. Another source of risk-taking behavior may be derived from the driver's gender. Interestingly, Table 2 demonstrates that male drivers are more likely to be involved in serious or fatal injury accidents (by 0.01 and 0.0232, respectively, as shown by the corresponding marginal effects) under favorable ambient conditions, such as daylight and fine weather. The latter conditions may provide the ideal ground for aggressive driving, which is generally more likely to be exhibited by male drivers (Fountas et al., 2019). In contrast, male drivers located in rural areas are more likely to be involved in slight-injury accidents (by 0.051, as shown by the corresponding marginal effect) occurred on lighted roadways under darkness and poor weather. These drivers are typically more familiar with roadways of lower design standards, as such, they may adjust their driving behavior accordingly in order to account for possible hazards stemming from inclement environmental conditions.

Vehicle-specific contributing factors

The involvement of a private passenger car in a single-vehicle accident in daylight and poor weather increases the probability of slight injuries (by 0.0627, as shown in Table 2), and consequently, decreases the probability of serious and fatal injuries (by -0.0614 and -0.0013, respectively). The involvement of a private passenger car or a taxi/hired car reduces the probability of high-severity injuries on unlighted roadways under darkness, regardless of the weather conditions. However, the effect is stronger in poor weather rather than in fine weather (the likelihood of slight injuries increases by 0.1282 in the former case, by 0.0995 in the latter). In contrast, the private passenger car indicator has a negative impact on accidents on lighted roadways: by decreasing the threshold between serious and fatal injuries in the model representing darkness and fine weather conditions, the involvement of passenger car increases the probability of a fatal injury (by 0.0878, as shown by the corresponding marginal effect in Table 3). This is consistent with previous studies that have acknowledged the heterogeneous effect of passenger cars on injury severities (e.g., Behnood and Mannering, 2015; Fountas et al., 2018b). The observed difference in the effect of passenger cars on accident injury severities may capture variations in behavioral responses to different lighting conditions. The presence of artificial lighting, ensuring better visibility, can result in more aggressive patterns, especially for passenger car drivers, who may also indulge in risk-taking behaviors. Focusing on other vehicle types, accidents involving motorcycles tend to have high-severity outcomes, especially in daylight and fine weather. Such relationship is intuitive and can be explained by the significant vulnerability of the motorcyclists when involved in single-vehicle accidents (Savolainen and Mannering, 2007; Huang et al., 2008; Shaheed and Gkritza, 2014; Waseem et al., 2019).

Vehicle age was also found to induce mixed effects on accident injury severities across different lighting and weather conditions. The involvement of an older vehicle in an accident occurred in daylight is found to result in an injury outcome of higher severity. Table 2 shows that the specific impact is consistent, regardless of the weather conditions. In contrast, very old vehicles (older than 15 years) increase the probability of a low severity outcome for accidents occurred in darkness and fine weather conditions on lighted roadways. This finding may capture the risk-compensating behavior of drivers who acknowledge the safety risks arising from the dark conditions and the lower safety performance of an old vehicle; as noted previously, such a behavior might be reflected through greater caution from the driver's side. Similarly, newer vehicles (with vehicle age less than 8 years) are also found to increase the probability of a slight injury (by 0.0713, as shown by the corresponding marginal effect in Table 4) in accidents occurred on unlighted roadways under darkness and fine weather. The advanced light and driver assistance systems of newer vehicles may be particularly effective in low-visibility conditions, thus mitigating the risk of severe injuries (Scanlon et al., 2017).

With regard to the impact of engine capacity, the involvement of vehicles with high-capacity engines (1800cc or more) is found to increase the probability of serious and fatal injuries for accidents occurred in daylight and fine weather conditions. This could be attributed to risk-taking driving typically exhibited by drivers of sports cars or powerful premium cars (Horswill and Coster, 2002) as well as to the difficulty to steer these vehicles, especially under extenuating driving circumstances. Previous research has identified significant heterogeneity in the effect of engine capacity in injury-severity outcomes (see, for example, the discussion provided in Seraneeprakam et al., 2017). Hence, this finding may be worth further investigation, especially from the perspective of manufacturing companies.

Trip-specific contributing factors

The trip purpose was identified as one of the major trip characteristics with influence on accident injury severities. Specifically, Table 3 shows that accidents occurred during work-related trips (i.e., when the trip is considered as an integral part of work) are associated with slight-injury outcomes under darkness and poor weather on lighted roadways. This relationship may pick up the effect of greater experience and familiarity with unfavorable environmental conditions, particularly for individuals who frequently drive for business-related purposes. In contrast, the work-related trips are found to decrease the threshold between serious and fatal injuries for accidents occurred in darkness and fine weather on lighted roadways causing a subsequent increase (by 0.096, as shown by the corresponding marginal effect) of the probability of fatal injuries. The specific effect could be attributed to personality-specific unobserved characteristics, which are captured – to some extent – by the variable representing the work-related trips. Such characteristics could possibly include work-generated pressure, rush to the destination or driver's fatigue, with all of them likely having a negative impact on driving behavior (Fountas et al., 2019). The conflicting impacts of work-related trips on injury severities constitute an indicative example of how the relaxation of the fixed ordered thresholds can shed light on unobserved variations that cannot be identified through the vectors of exogenous variables (**X**s) in the ordered probability function. Similar unobserved effects may also determine the negative effect of the commuting trips on the threshold between serious and fatal injuries in the model for accidents on lighted roadways under darkness and poor weather.

Accidents occurred in the morning slot are more likely to belong in the minor-injury state when ambient daylight conditions are present; it should be noted that the variables representing a morning slot were found statistically significant for either fine or poor weather. The opposite applies for accidents occurred in late night (between midnight and 6.00 am) on unlighted roadways, which are more likely to result in severe injuries under the impact of darkness and fine weather conditions. This constitutes another indication of risk-taking patterns of drivers, either due to low traffic volumes or due to their impaired cognitive functions in late night. The threshold between serious and fatal injuries is higher for accidents occurred during the weekend under daylight and poor weather conditions leading to a slight increase in the probability of serious injuries (by 0.0001, as shown by the corresponding marginal effect in Table 2). A similar effect is also observed in the model developed for dark and poor weather conditions on lighted roadways, where the weekend indicator increases the probability of a serious injury (by 0.0655, as shown in Table 3). When darkness and fine weather conditions are present on unlighted roadways, the variable representing accidents occurred on Sundays is found to increase the probability of serious and fatal injuries (by 0.123 and 0.061, respectively, as shown by the marginal effects in Table 4). The overall propensity of weekend-related accidents to severe injuries is in line with previous research findings (see, for example, Gray et al., 2008; Yu et al., 2019) and could be attributed to drug- or alcohol-impaired driving, which is much more evident during the weekends in the UK (Department for Transport, 2017). In addition, the traffic conditions that are typically observed in weekends are more conducive to committing aggressive driving violations, which can in turn cause high-severity accidents.

Location-specific factors

Various location-specific indicators were also investigated and found to affect accident injury severities. Accidents occurred within the city of Edinburgh were found more likely to result in slight injuries in the model for darkness and poor weather conditions on lighted roadways as well as in the model for daylight and fine weather conditions. Edinburgh is a city with intense traffic flows, especially during the commuting hours, and generally low speed limits. Over the last few years, a 20 mph speed limit has been implemented in the central network of the city, made up of local, collector and minor arterial roads. The identified propensity for low-severity accidents could be substantiated by the low-speed traffic patterns typically observed in the city. The variable indicating unlighted locations in the county of Highlands and Islands or in the county of Moray is found to decrease the threshold in the model representing darkness and fine weather, and in turn, to increase the probability of fatal injuries by 0.0412 (as shown by the corresponding marginal effect in Table 4). These counties are located in North Scotland where various discrepancies in safety, maintenance, and quality of the local roadway infrastructure have been identified over the last decades (Scottish Government, 2009; Audit Scotland, 2016). The specific finding could be also associated with the persistent trends of alcohol-impaired driving, which are largely observed in these areas.

MODEL EVALUATION

To statistically determine whether the zero-inflated hierarchical ordered probit model can better account for the preponderance of slight-injury observations compared to lower-order model counterparts (i.e., ordered probit model and hierarchical ordered probit model), a Vuong test was conducted. The specific test (Vuong, 1989) is extensively employed in cases of comparisons between non-nested modeling approaches. The test is performed in two stages; firstly, we calculated the *m* statistic for each accident observation as follows (Vuong, 1989; Washington et al., 2011; Anastasopoulos, 2016):

$$m_i = LN\,[\varphi_{mc}(k_i \mid \mathbf{X}_i) / \varphi_{zio}(k_i \mid \mathbf{X}_i)] \tag{7}$$

Where, $\varphi_{\mathrm{mc}}(k_{\mathrm{i}}|\mathbf{X}_{\mathrm{i}})$ and $\varphi_{\mathrm{zio}}(k_{\mathrm{i}}|\mathbf{X}_{\mathrm{i}})$ represent the probability density functions of the considered model counterpart and of the zero-inflated hierarchical ordered probit model, respectively. Then, possible statistically significant differences in the predictions provided by the two models are identified through the calculation of the Vuong's statistic (Vuong, 1989; Anastasopoulos, 2016):

$$V = \frac{\overline{m}\sqrt{N}}{\sigma_m} \tag{8}$$

Where $\overline{m}$ and σ_{m} denote the mean and the standard deviation of the distribution of the *m* statistic, whereas *N* represents the number of observations. Considering a 95% level of confidence (for which, V_{critical}=1.96), large negative values (lower than -1.96) substantiate the appropriateness of the zero-inflated approach over the compared counterpart (Fountas and Anastasopoulos, 2018). To conduct the test, we estimated the ordered probit and hierarchical ordered probit counteparts using the same independent variables included in the zero-inflated hierarchical ordered probit models. Tables 2-4 provide the calculated values of the Vuong test for all the estimated models. Across all combinations of weather and lighting conditions, the Vuong test results substantiate the appropriateness of the zero-inflated models.

To further compare the statistical performance of the zero-inflated hierarchical ordered probit model with correlated disturbances (ZIHOPITCD) with the ordered probit (OP) and the hierarchical ordered probit (HOPIT) models, various goodness-of-fit measures were computed, namely the log-likelihood at convergence, AIC and BIC. These values are provided in the lower sections of Tables 2-4. Overall, the comparative evaluation of the goodness-of-fit metrics reaffirms the statistical superiority of the chosen approach, as, in almost all cases, the zero-inflated hierarchical ordered probit model with correlated disturbances yields the lowest metric values.[6]

The correlation between the disturbance terms of the binary probit and ordered probit components was found to be statistically significant and strong in magnitude in all models. This demonstrates the appropriateness of the employed bivariate normal distribution of disturbance terms to capture systematic variations of unobserved characteristics between the minor and ordered injury states. These variations may reflect similarities in the drivers' responses against various environmental conditions, especially in cases of low-severity accidents. Note that such driver-specific behavioral traits cannot be explicitly observed through the employed dataset, but they definitely have a pronounced effect on the accident generation mechanism (Mannering et al., 2016).

SUMMARY AND CONCLUSIONS

This study aimed at identifying the joint effect of weather and lighting conditions on the generation mechanism of single-vehicle accidents. Owing to the visibility- and roadway

[6] Note that lower values of the log-likelihood at convergence, AIC and BIC imply better statistical performance of the model under consideration (Washington et al., 2011).

condition-related challenges induced by various combinations of these characteristics, the determinants of injury severities are likely to vary. To identify these variations, we estimated several injury-severity models for various combinations of weather and lighting conditions by employing a zero-inflated hierarchical ordered probit approach with correlated disturbances. This approach allows accounting for two regimes of the injury-severity mechanism (i.e., the minor-injury state and the ordered injury state) and for capturing the effect of commonly shared unobserved characteristics among these regimes, through the correlated structure of the disturbance terms. The incorporation of the hierarchical ordered structure relaxed the fixed threshold restriction enabling the identification of – typically unobserved – exogenous variables that determine the ordered thresholds.

Using data from injury accidents occurred in Scotland from 2016 through 2017, and considering three injury severity outcomes (slight injury, serious injury and fatal injury), the effects of various accident-, vehicle-, driver-, roadway-, trip-, and location-specific characteristics were investigated. The results of various likelihood ratio tests showed that the effects of these characteristics on accident injury severities are statistically different across various combinations of natural lighting (daylight vs darkness), weather (fine vs poor), and roadway lighting (lighted roadways vs unlighted roadways) conditions. Overall, skidding vehicles, high-speed roadways, high engine capacities of vehicles, tree-related collisions, and pedestrian involvement constitute influential factors that were found to have consistent effects on accident injury severities across all lighting and weather combinations. In contrast, passenger vehicles, vehicle age, run-off-the-road vehicles, driver age and gender, pavement surface condition, and work-related trips were found to have varying effects across such combinations, in terms of sign and magnitude. The correlation coefficient of the disturbance terms corresponding to the two injury-severity states was found to be statistically significant in all models, thus implying the strong interdependence of the unobserved variations that may affect both states.

It is acknowledged that the empirical findings of the analysis may be subject to possible data-specific biases, primarily arising from limitations of the accident reporting system (as, for example, the omission of no-injury accidents). Despite this possibility, the identified variations in the effect of injury-severity determinants across different lighting and weather conditions can provide useful input for communication technologies seeking to optimize driver's response to external stimuli with high accident risk. Such technologies may refer to driver assistance systems as well as to vehicle-to-infrastructure or inter-vehicle communication systems that can be leveraged in conditionally or fully autonomous vehicles. The safety implications of such technologies may be more evident when driving in areas typically encountering significant fluctuations of weather and lighting conditions. Hence, future research could be devoted to the incorporation of more disaggregate spatial effects; this will shed more light on an additional aspects of unobserved heterogeneity that could not be explicitly explored through the employed methodological framework.

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Table 1. Descriptive statistics of key variables

Variable description	Mean or % of 1	Min	Max
Accident location indicator (1 if the accident occurred in the county of Highlands and Islands or in the county of Moray, 0 otherwise) [DRNLF]	9.79%	0	1
Accident location indicator (1 if the accident occurred within the city of Aberdeen, 0 otherwise) [DRLTF]	4.74%	0	1
Accident location indicator (1 if the accident occurred within the city of Edinburgh, 0 otherwise) [DF]	15.67%	0	1
Accident location indicator (1 if the accident occurred within the city of Edinburgh, 0 otherwise) [DRLTP]	13.88%	0	1
Animal indicator (1 if an animal was involved in the accident, 0 otherwise) [DF]	1.20%	0	1
Day-of-the-accident indicator (1 if the accident occurred during the weekend, 0 otherwise) [DP]	31.51%	0	1
Day-of-the-accident indicator (1 if the accident occurred during the weekend, 0 otherwise) [DRLTP]	37.85%	0	1
Day-of-the-accident indicator (1 if the accident occurred on Sunday, 0 otherwise) [DRNLF]	18.41%	0	1
Driver's age indicator (1 if the driver was older than 23 years old but younger than 37 years old, 0 otherwise) [DRNLF]	29.60%	0	1
Driver's age indicator (1 if the driver was older than 45 years old, 0 otherwise) [DRLTP]	35.65%	0	1
Driver's age indicator (1 if the driver was younger than 23 years old, 0 otherwise) [DF]	19.24%	0	1
Driver's age indicator (1 if the driver was younger than 27 years old, 0 otherwise) [DP]	30.73%	0	1
Driver's gender and home area indicator (1 if female driver whose residence is located in an urban area, 0 otherwise) [DRNLF]	7.93%	0	1
Driver's gender indicator (1 if male, 0 otherwise) [DF]	64.79%	0	1
Driver's home area indicator (1 if the driver's home area is rural, 0 otherwise) [DF]	17.95%	0	1
Engine capacity indicator (1 if capacity of vehicle engine is 1800cc or greater, 0 otherwise) [DF]	28.72%	0	1
Intersection indicator (1 if the accident occurred on a T-junction or crossroads, 0 otherwise) [DRNLF]	6.99%	0	1
Intersection indicator (1 if the accident occurred on an intersection or an intersection was present within 20 metres from the accident location, 0 otherwise) [DRLTP]	44.16%	0	1
Inverse of the driver's age (1/years) [DRLTF]	0.0300	0.0110	0.0625
Inverse of the vehicle's engine capacity (cc^{-1}) [DRNLP]	0.001	0.0001	0.0081
Off-the-road object indicator (1 if the vehicle hit a permanent object off the roadway, 0 otherwise) [DP]	4.80%	0	1
Off-the-road object indicator (1 if the vehicle struck a tree off the roadway, 0 otherwise) [DF]	4.18%	0	1
Off-the-road object indicator (1 if the vehicle struck a tree off the roadway, 0 otherwise) [DP]	7.62%	0	1
Off-the-road object indicator (1 if the vehicle struck a tree off the roadway, 0 otherwise) [DRNLF]	12.12%	0	1
On-road object indicator (1 if the vehicle hit a curb within the roadway, 0 otherwise) [DF]	10.06%	0	1
Pavement surface condition (1 if the pavement was dry at the time of the accident, 0 otherwise) [DP]	7.80%	0	1

Pavement surface condition (1 if the pavement was dry at the time of the accident, 0 otherwise) [DRLTF]	63.16%	0	1
Pavement surface condition (1 if the pavement was dry at the time of the accident, 0 otherwise) [DRNLF]	50.58%	0	1
Pavement surface condition (1 if the pavement was wet at the time of the accident, 0 otherwise) [DRNLP]	69.58%	0	1
Pedestrian indicator (1 if a pedestrian was involved in the accident, 0 otherwise) [DF]	54.66%	0	1
Pedestrian indicator (1 if a pedestrian was involved in the accident, 0 otherwise) [DP]	49.63%	0	1
Pedestrian indicator (1 if a pedestrian was involved in the accident, 0 otherwise) [DRNLP]	8.75%	0	1
Pedestrian indicator (1 if a pedestrian was involved in the accident, 0 otherwise) [DRNLF]	14.22%	0	1
Point-of-impact indicator (1 if the first point of impact was on the front of the vehicle, 0 otherwise) [DRLTF]	59.21%	0	1
Point-of-impact indicator (1 if the first point of impact was on the front of the vehicle, 0 otherwise) [DRNLF]	12.12%	0	1
Roadway type indicator (1 if the accident occurred on a dual carriageway, 0 otherwise) [DP]	11.71%	0	1
Roadway type indicator (1 if the accident occurred on a one-way road, 0 otherwise) [DRLTF]	4.74%	0	1
Roadway type indicator (1 if the accident occurred on a rural single carriageway, 0 otherwise) [DF]	33.24%	0	1
Roadway type indicator (1 if the accident occurred on a rural single carriageway, 0 otherwise) [DRNLP]	76.05%	0	1
Roadway type indicator (1 if the accident occurred on a single carriageway, 0 otherwise) [DRLTP]	75.39%	0	1
Roadway type indicator (1 if the accident occurred on an urban dual carriageway, 0 otherwise) [DRNLF]	3.03%	0	1
Roadway type indicator (1 if the accident occurred on an urban single carriageway, 0 otherwise) [DRNLF]	7.93%	0	1
Rural area indicator (1 if the accident occurred in a rural area, 0 otherwise) [DRNLF]	88.81%	0	1
Skidding and overturning indicator (1 if the vehicle skidded and overturned during the accident, 0 otherwise) [DRNLF]	20.51%	0	1
Skidding indicator (1 if the vehicle skidded during the accident, 0 otherwise) [DF]	82.90%	0	1
Skidding indicator (1 if the vehicle skidded during the accident, 0 otherwise) [DP]	13.10%	0	1
Speed limit (in mph) [DF]	38.16	20	70
Speed limit indicator (1 if speed limit greater than 30 mph, 0 otherwise) [DP]	38.66%	0	1
Speed limit indicator (1 if speed limit greater than 30 mph, 0 otherwise) [DRLTF]	11.58%	0	1
Speed limit indicator (1 if speed limit greater than 30 mph, 0 otherwise) [DRLTP]	11.99%	0	1
Speed limit indicator (1 if speed limit greater than 40 mph, 0 otherwise) [DRNLP]	85.93%	0	1
Speed limit indicator (1 if speed limit greater than 30 mph, 0 otherwise) [DRNLF]	90.44%	0	1
Time-of-the-day indicator (1 if the accident occurred between 6 and 9.30 am, 0 otherwise) [DP]	14.75%	0	1
Time-of-the-day indicator (1 if the accident occurred between 8.30 and 9.30 am, 0 otherwise) [DF]	9.59%	0	1

Time-of-the-day indicator (1 if the accident occurred between midnight and 6.00 am, 0 otherwise) [DRNLF]	30.30%	0	1
Trip purpose indicator (1 if the accident occurred during a commute-related trip, 0 otherwise) [DRLTP]	18.61%	0	1
Trip purpose indicator (1 if the accident occurred during a work-related trip, 0 otherwise) [DRLTF]	20.79%	0	1
Trip purpose indicator (1 if the accident occurred during a work-related trip, 0 otherwise) [DRLTP]	22.40%	0	1
Vehicle age indicator (1 if the vehicle is less than 8 years old, 0 otherwise) [DRNLF]	53.61%	0	1
Vehicle age indicator (1 if the vehicle is older than 15 years, 0 otherwise) [DRLTF]	3.68%	0	1
Vehicle age indicator (1 if the vehicle is older than 12 years, 0 otherwise) [DP]	13.34%	0	1
Vehicle age indicator (1 if the vehicle is older than 9 years, 0 otherwise) [DF]	25.80%	0	1
Vehicle location indicator (1 if the vehicle was clearing an intersection or was waiting at an intersection exit at the time of the accident, 0 otherwise) [DRLTF]	11.18%	0	1
Vehicle maneuver indicator (1 if the vehicle was going straight ahead at the time of the accident, 0 otherwise) [DRLTF]	58.42%	0	1
Vehicle maneuver indicator (1 if the vehicle was reversing at the time of the accident, 0 otherwise) [DF]	5.44%	0	1
Vehicle maneuver indicator (1 if the vehicle was reversing at the time of the accident, 0 otherwise) [DP]	4.16%	0	1
Vehicle position indicator (1 if the vehicle left the roadway nearside at the time of the accident, 0 otherwise) [DP]	17.25%	0	1
Vehicle position indicator (1 if the vehicle left the roadway offside at the time of the accident, 0 otherwise) [DF]	10.67%	0	1
Vehicle position indicator (1 if the vehicle left the roadway offside at the time of the accident, 0 otherwise) [DRLTF]	7.37%	0	1
Vehicle position indicator (1 if the vehicle left the roadway offside at the time of the accident, 0 otherwise) [DRLTP]	5.05%	0	1
Vehicle type indicator (1 if motorcycle, 0 otherwise) [DF]	9.65%	0	1
Vehicle type indicator (1 if bus or mini-bus, 0 otherwise) [DP]	6.41%	0	1
Vehicle type indicator (1 if private passenger car, 0 otherwise) [DP]	70.86%	0	1
Vehicle type indicator (1 if pedal cycle, 0 otherwise) [DF]	1.73%	0	1
Vehicle type indicator (1 if private passenger car or taxi/hired car, 0 otherwise) [DRNLP]	83.65%	0	1
Vehicle type indicator (1 if private passenger car or taxi/hired car, 0 otherwise) [DRNLF]	82.52%	0	1
Vehicle type indicator (1 if private passenger car, 0 otherwise) [DRLTF]	75.53%	0	1

[DF]: Daylight and fine weather [DRLTF]: Darkness and fine weather on lighted roadways
[DP]: Daylight and poor weather [DRLTP]: Darkness and poor weather on lighted roadways
[DRNLF]: Darkness and fine weather on unlighted roadways
[DRNLP]: Darkness and poor weather on unlighted roadways

Table 2. Model estimation results and marginal effects of accident injury severities under daylight and fine weather and under daylight and poor weather.

Variable description	Daylight and fine weather					Daylight and poor weather				
	Parameter Estimate	*t*-stat	*Marginal effects*			Parameter Estimate	*t*-stat	*Marginal effects*		
			Slight Injury	Serious Injury	Fatal injury			Slight Injury	Serious Injury	Fatal injury
Ordered injury state										
Constant	-0.767	-5.54	-	-	-	-	-	-	-	-
Vehicle type indicator (1 if motorcycle, 0 otherwise)	0.841	7.53	-0.1873	-0.0365	0.2238	-	-	-	-	-
Vehicle type indicator (1 if pedal cycle, 0 otherwise)	1.001	4.54	-0.1941	-0.0891	0.2832	-	-	-	-	-
Vehicle type indicator (1 if private passenger car, 0 otherwise)	-	-	-	-	-	-1.116	-9.13	0.0627	-0.0614	-0.0013
Vehicle age indicator (1 if the vehicle is older than 9 years, 0 otherwise)	0.145	2.43	-0.0407	0.0099	0.0308	-	-	-	-	-
Vehicle age indicator (1 if the vehicle is older than 12 years, 0 otherwise)	-	-	-	-	-	0.432	2.76	-0.0167	0.0165	0.0001
Pedestrian indicator (1 if a pedestrian was involved in the accident, 0 otherwise)	0.466	7.04	-0.1358	0.0432	0.0925	0.613	3.68	-0.0219	0.0214	0.0005
Off-the-road object indicator (1 if the vehicle struck a tree off the roadway, 0 otherwise)	0.454	3.66	-0.1126	0.0020	0.1107	1.537	7.45	-0.1382	0.1355	0.0027
Roadway type indicator (1 if the accident occurred on a dual carriageway, 0 otherwise)	-	-	-	-	-	0.377	2.25	-0.0149	0.0148	0.0001
Accident location indicator (1 if the accident occurred within the city of Edinburgh, 0 otherwise)	-0.161	-2.01	0.0476	-0.0162	-0.0314	-	-	-	-	-
Driver's gender indicator (1 if male, 0 otherwise)	0.115	1.91	-0.0332	0.0100	0.0232	-	-	-	-	-
Driver's age indicator (1 if the driver was younger than 23 years old, 0 otherwise)	-0.168	-2.45	0.0497	-0.0167	-0.0329	-	-	-	-	-
Skidding indicator (1 if the vehicle skidded during the accident, 0 otherwise)	-	-	-	-	-	-0.717	-5.04	0.0176	-0.0175	-0.0001

Variable description	Daylight and fine weather					Daylight and poor weather				
	Parameter Estimate	*t*-stat	*Marginal effects*			Parameter Estimate	*t*-stat	*Marginal effects*		
			Slight Injury	Serious Injury	Fatal injury			Slight Injury	Serious Injury	Fatal injury
Vehicle position indicator (1 if the vehicle left the roadway offside at the time of the accident, 0 otherwise)	0.159	1.78	-0.0438	0.0092	0.0346	-	-	-	-	-
Minor-injury state										
Driver's age indicator (1 if the driver was younger than 27 years old, 0 otherwise)	-	-	-	-	-	0.618	6.01	0.0180	-0.0180	0.0000
Time-of-the-day indicator (if the accident occurred between 8.30 and 9.30 am, 0 otherwise)	0.590	2.83	0.0805	-0.0731	-0.0074	-	-	-	-	-
Time-of-the-day indicator (if the accident occurred between 6 and 9.30 am, 0 otherwise)	-	-	-	-	-	0.763	6.36	0.0173	-0.0173	0.0000
Engine capacity indicator (1 if the capacity of the vehicle's engine is 1800cc or greater, 0 otherwise)	-0.470	-2.23	-0.0412	0.0383	0.0029	-	-	-	-	-
Off-the-road object indicator (1 if the vehicle hit a permanent object off the roadway, 0 otherwise)	-	-	-	-	-	1.109	3.85	0.0147	-0.0147	0.0000
Animal indicator (1 if an animal was involved in the accident, 0 otherwise)	1.115	1.74	0.1984	-0.1744	-0.0240	-	-	-	-	-
Speed limit (in mph)	-0.029	-2.92	-0.0075	0.0063	0.0012	-	-	-	-	-
Vehicle maneuver indicator (1 if the vehicle was reversing at the time of the accident, 0 otherwise)	0.442	2.16	0.0571	-0.0520	-0.0051	0.851	2.49	0.0151	-0.0151	0.0000
Vehicle type indicator (1 if bus or mini-bus, 0 otherwise)	-	-	-	-	-	0.694	2.23	0.0173	-0.0173	0.0000
Pavement surface condition (1 if the pavement was dry at the time of the accident, 0 otherwise)	-	-	-	-	-	0.773	4.53	0.0150	-0.0150	0.0000
Threshold-specific variables										
Driver's home area indicator (1 if the driver's home area is rural, 0 otherwise)	-0.164	-1.75	-	-0.0524	0.0524	-	-	-	-	-

Variable description	**Daylight and fine weather**					**Daylight and poor weather**				
			Marginal effects					*Marginal effects*		
	Parameter Estimate	*t*-stat	Slight Injury	Serious Injury	Fatal injury	Parameter Estimate	*t*-stat	Slight Injury	Serious Injury	Fatal injury
Skidding indicator (1 if the vehicle skidded during the accident, 0 otherwise)	0.376	3.17	-	0.1007	-0.1007	-	-	-	-	-
On-road object indicator (1 if the vehicle hit a curb within the roadway, 0 otherwise)	-0.517	-2.72	-	-0.1635	0.1635	-	-	-	-	-
Roadway type indicator (1 if the accident occurred on a rural single carriageway, 0 otherwise)	-0.245	-2.73	-	-0.0782	0.0782	-	-	-	-	-
Speed limit indicator (1 if speed limit greater than 30 mph, 0 otherwise)	-	-	-	-	-	-0.594	-3.81	-	-0.0001	0.0001
Vehicle position indicator (1 if the vehicle left the roadway nearside at the time of the accident, 0 otherwise)	-	-	-	-	-	0.447	2.74	-	0.0001	-0.0001
Day-of-the-accident indicator (1 if the accident occurred during the weekend, 0 otherwise)	-	-	-	-	-	0.452	1.95	-	0.0001	-0.0001
Intercept for μ_1	0.520	5.99	-	-	-	0.805	7.13	-	-	-
Correlation of disturbance terms	-0.566	-3.44	-	-	-	0.999	42.41	-	-	-
Model Evaluation										
Goodness-of-fit metrics	OP		HOPIT	ZIHOPITCD		OP		HOPIT	ZIHOPITCD	
Number of observations (N)	2892		2892	2892		814		814	814	
Number of estimable parameters (K)	11		15	21		7		10	17	
Restricted log-likelihood, $LL(0)$	-1913.731		-1913.731	-1913.731		-493.610		-493.610	-493.610	
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-1823.710		-1807.930	-1781.756		-485.959		-480.451	-428.054	
AIC [$AIC=2K\text{-}2LL(\boldsymbol{\beta})$]	3669.420		3645.860	3605.512		985.918		980.902	890.108	
BIC [$BIC = -2LL(\boldsymbol{\beta}) + K\ln(N)$]	3735.087		3735.406	3730.876		1018.832		1027.922	970.0413	
Vuong test statistic										
ZIOPITCD vs OP			4.638					-4.332		
ZIOPITCD vs HOPIT			-3.655					-4.018		

OP: Ordered Probit; HOPIT: Hierarchical Ordered Probit; ZIHOPITCD: Zero-inflated hierarchical ordered probit with correlated disturbances

Table 3. Model estimation results and marginal effects of accident injury severities under darkness and fine weather on lighted roadways and under darkness and poor weather on lighted roadways.

Variable description	**Darkness and fine weather on lighted roadways**					**Darkness and poor weather on lighted roadways**				
	Parameter Estimate	*t*-stat	*Marginal effects*			Parameter Estimate	*t*-stat	*Marginal effects*		
			Slight Injury	Serious Injury	Fatal injury			Slight Injury	Serious Injury	Fatal injury
Ordered injury state										
Constant	0.746	6.21	-	-	-	-0.628	-4.00	-	-	-
Roadway type indicator (1 if the accident occurred on a one-way road, 0 otherwise)	-0.424	-2.46	0.1403	-0.0972	-0.0431	-	-	-	-	-
Roadway type indicator (1 if the accident occurred on a rural single carriageway, 0 otherwise)	-	-	-	-	-	-1.033	-2.57	0.0549	-0.0549	0.0000
Intersection indicator (1 if the accident occurred on an intersection or an intersection was present within 20 metres from the accident location, 0 otherwise)	-	-	-	-	-	-0.474	-2.64	0.0718	-0.0717	-0.0001
Inverse of the driver's age (1/years)	0.335	1.92	-0.0278	-0.0293	0.0571	-	-	-	-	-
Driver's age indicator (1 if the driver was older than 45 years old, 0 otherwise)	-	-	-	-	-	-0.469	-2.37	0.0606	-0.0606	0.0000
Driver's gender and residence area indicator (1 if male driver whose residence is located in a rural area, 0 otherwise)	-	-	-	-	-	-0.668	-1.72	0.0510	-0.0509	-0.0001
Vehicle age indicator (1 if the vehicle is older than 15 years, 0 otherwise)	-0.713	-2.48	0.2379	-0.1786	-0.0592	-	-	-	-	-
Vehicle location indicator (1 if the vehicle was clearing an intersection or was waiting at an intersection exit at the time of the accident, 0 otherwise)	-0.375	-2.71	0.1223	-0.0823	-0.0400	-	-	-	-	-
Vehicle maneuver indicator (1 if the vehicle was going straight ahead at the time of the accident, 0 otherwise)	0.205	2.23	-0.0271	-0.0035	0.0306	-	-	-	-	-

Variable description	Darkness and fine weather on lighted roadways					Darkness and poor weather on lighted roadways				
	Parameter Estimate	*t*-stat	*Marginal effects*			Parameter Estimate	*t*-stat	*Marginal effects*		
			Slight Injury	Serious Injury	Fatal injury			Slight Injury	Serious Injury	Fatal injury
Vehicle position indicator (1 if the vehicle left the roadway offside at the time of the accident, 0 otherwise)	-0.378	-2.40	0.1234	-0.0835	-0.0399	-	-	-	-	-
Trip purpose indicator (1 if the accident occurred during a work-related trip, 0 otherwise)	-	-	-	-	-	-0.513	-2.20	0.0556	-0.0555	-0.0001
Day-of-the-accident indicator (1 if the accident occurred during the weekend, 0 otherwise)	-	-	-	-	-	0.411	2.06	-0.0655	0.0655	0.0000
Minor-injury state										
Speed limit indicator (1 if speed limit greater than 30 mph, 0 otherwise)	-0.210	-1.78	-0.0207	0.0207	0.0000	-	-	-	-	-
Point-of-impact indicator (1 if the first point of impact was on the front of the vehicle, 0 otherwise)	-0.265	-3.18	-0.0265	0.0265	0.0000	-	-	-	-	-
Vehicle position indicator (1 if the vehicle left the roadway offside at the time of the accident, 0 otherwise)	-	-	-	-	-	1.451	2.86	0.0551	-0.0551	0.0000
Pavement surface condition (1 if the pavement was dry at the time of the accident, 0 otherwise)	0.152	1.91	0.0377	-0.0376	-0.0001	-	-	-	-	-
Accident location indicator (1 if the accident occurred within the city of Aberdeen, 0 otherwise)	-0.434	-1.82	-0.0230	0.02308	0.0000	-	-	-	-	-
Accident location indicator (1 if the accident occurred within the city of Edinburgh, 0 otherwise)	-	-	-	-	-	1.192	4.54	0.0598	-0.0598	0.0000
Threshold-specific variables										
Vehicle type indicator (1 if private passenger car, 0 otherwise)	-0.405	-1.80	-	-0.0878	0.0878	-	-	-	-	-

Variable description	Darkness and fine weather on lighted roadways					Darkness and poor weather on lighted roadways				
	Parameter Estimate	*t*-stat	*Marginal effects*			Parameter Estimate	*t*-stat	*Marginal effects*		
			Slight Injury	Serious Injury	Fatal injury			Slight Injury	Serious Injury	Fatal injury
Trip purpose indicator (1 if the accident occurred during a work-related trip, 0 otherwise)	-0.436	-2.36	-	-0.0960	0.0960	-	-	-	-	-
Trip purpose indicator (1 if the accident occurred during a commuting trip, 0 otherwise)	-	-	-	-	-	-0.741	-2.13	-	-0.0001	0.0001
Intercept for μ_1	0.483	1.77	-	-	-	0.810	5.55	-	-	-
Correlation of disturbance terms	-0.992	-51.20	-	-	-	0.999	6.69	-	-	-
Model Evaluation										
Goodness-of-fit metrics	OP		HOPIT	ZIHOPITCD		OP		HOPIT	ZIHOPITCD	
Number of observations (*N*)	752		752	752		317		317	317	
Number of estimable parameters (*K*)	8		10	15		8		9	12	
Restricted log-likelihood, $LL(0)$	-514.886		-514.886	-514.886		-189.054		-189.054	-189.054	
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-501.902		-495.560	-478.321		-180.400		-179.014	-171.867	
AIC [AIC=2K-2$LL(\boldsymbol{\beta})$]	1019.804		1011.120	986.642		382.800		376.028	367.734	
BIC [$BIC = -2LL(\boldsymbol{\beta}) + K\ln(N)$]	1056.786		1057.347	1055.983		412.871		409.858*	412.841*	
Vuong test statistic										
ZIOPITCD vs OP			-3.227					-2.586		
ZIOPITCD vs HOPIT			-3.009					-1.860**		

OP: Ordered Probit; HOPIT: Hierarchical Ordered Probit; ZIHOPITCD: Zero-inflated hierarchical ordered probit with correlated disturbances

*To further compare the statistical performance of the hierarchical ordered probit (HOPIT) and the zero-inflated hierarchical ordered probit model with correlated disturbances (ZIHOPITCD), the corrected AIC [AICC = AIC + 2 K(K + 1)/(N-K-1] was also calculated. Corrected AIC can account for the impact of estimable parameters as it penalizes models with higher number of estimable parameters (Anastasopoulos, 2016; Fountas and Anastasopoulos, 2018). Corrected AIC for HOPIT model is equal to 376.614, while corrected AIC for the ZIHOPITCD model is equal to 368.7603; the lower value of the corrected AIC for the ZIHOPITCD model indicates its better statistical performance relative to the HOPIT model.

**The specific Vuong test statistic is statistically significant at a 0.90 level of confidence.

Table 4. Model estimation results and marginal effects of accident injury severities under darkness and fine weather on unlighted roadways and under darkness and poor weather on unlighted roadways.

Variable description	**Darkness and fine weather on unlighted roadways**					**Darkness and poor weather on unlighted roadways**				
			Marginal effects					*Marginal effects*		
	Parameter Estimate	*t*-stat	Slight Injury	Serious Injury	Fatal injury	Parameter Estimate	*t*-stat	Slight Injury	Serious Injury	Fatal injury
Ordered injury state										
Roadway type indicator (1 if the accident occurred on an urban dual carriageway, 0 otherwise)	-1.665	-1.78	0.1560	-0.1298	-0.0262	-	-	-	-	-
Roadway type indicator (1 if the accident occurred on a rural single carriageway, 0 otherwise)	-	-	-	-	-	-0.419	-2.65	0.1378	-0.1148	-0.0229
Pedestrian indicator (1 if a pedestrian was involved in the accident, 0 otherwise)	1.286	3.63	-0.2040	0.1210	0.0830	1.067	3.30	-0.3852	0.2852	0.1000
Driver's age indicator (1 if the driver was older than 23 years old but younger than 37 years old, 0 otherwise)	0.643	2.77	-0.0978	0.0694	0.0284	-	-	-	-	-
Vehicle age indicator (1 if the vehicle is less than 8 years old, 0 otherwise)	-0.490	-2.67	0.0713	-0.0523	-0.0190	-	-	-	-	-
Vehicle type indicator (1 if private passenger car or taxi/hired car, 0 otherwise)	-0.660	-3.29	0.0995	-0.0677	-0.0318	-0.392	-2.53	0.1282	-0.1047	-0.0235
Inverse of the vehicle's engine capacity (cc^{-1})	-	-	-	-	-	0.563	1.73	-0.1954	0.1499	0.0455
Off-the-road object indicator (1 if the vehicle struck a tree off the roadway, 0 otherwise)	0.708	2.28	-0.1097	0.0723	0.0374	-	-	-	-	-
Skidding and overturning indicator (1 if the vehicle skidded and overturned during the accident, 0 otherwise)	-0.570	-2.07	0.0779	-0.0615	-0.0164	-	-	-	-	-
Day-of-the-accident indicator (1 if the accident occurred on Sunday, 0 otherwise)	1.133	3.43	-0.1844	0.1233	0.0611	-	-	-	-	-
Time-of-the-day indicator (1 if the accident occurred between midnight and 6.00 am, 0 otherwise)	0.663	2.71	-0.1033	0.0759	0.0274	-	-	-	-	-

Variable description	Darkness and fine weather on unlighted roadways					Darkness and poor weather on unlighted roadways				
	Parameter Estimate	*t*-stat	*Marginal effects*			Parameter Estimate	*t*-stat	*Marginal effects*		
			Slight Injury	Serious Injury	Fatal injury			Slight Injury	Serious Injury	Fatal injury
Minor-injury state										
Speed limit indicator (1 if speed limit greater than 30 mph, 0 otherwise)	-1.510	-2.69	-0.1621	0.1381	0.0239	-	-	-	-	-
Speed limit indicator (1 if speed limit greater than 40 mph, 0 otherwise)	-	-	-	-	-	-1.312	-3.66	-0.0042	0.0042	0.0000
Rural area indicator (1 if the accident occurred in a rural area, 0 otherwise)	1.705	3.00	0.2448	-0.1891	-0.0557	-	-	-	-	-
Driver's gender and residence area indicator (1 if female driver whose residence is located in an urban area, 0 otherwise)	1.192	2.35	0.1453	-0.1241	-0.0212	-	-	-	-	-
Pavement surface condition (1 if the pavement was dry at the time of the accident, 0 otherwise)	-0.551	-2.39	-0.0936	0.0771	0.0165	-	-	-	-	-
Pavement surface condition (1 if the pavement was wet at the time of the accident, 0 otherwise)	-	-	-	-	-	-1.470	-2.71	-0.0140	0.0140	0.0000
Threshold-specific variables										
Roadway type indicator (1 if the accident occurred on an urban single carriageway, 0 otherwise)	0.404	1.96	-	0.0194	-0.0194	-	-	-	-	-
Point-of-impact indicator (1 if the first point of impact was on the front of the vehicle, 0 otherwise)	0.614	2.36	-	0.0233	-0.0233	-	-	-	-	-
Intersection indicator (1 if the accident occurred on a T-junction or crossroads, 0 otherwise)	0.410	1.85	-	0.0188	-0.0188	-	-	-	-	-
Accident location indicator (1 if the accident occurred in the county of Highlands and Islands or in the county of Moray, 0 otherwise)	-0.596	-1.80	-	-0.0412	0.0412	-	-	-	-	-
Accident location indicator (1 if the accident occurred in the Angus county, 0 otherwise)	-	-	-	-	-	-1.712	-1.84	-	-0.1780	0.1780
Intercept for μ_1	0.427	2.99	-	-	-	0.529	2.96	-	-	-
Correlation of disturbance terms	0.624	2.02	-	-	-	-0.999	-3.95	-	-	-

<table>
<tr><th rowspan="3">Variable description</th><th colspan="5">Darkness and fine weather on unlighted roadways</th><th colspan="5">Darkness and poor weather on unlighted roadways</th></tr>
<tr><th rowspan="2">Parameter Estimate</th><th rowspan="2">t-stat</th><th colspan="3">Marginal effects</th><th rowspan="2">Parameter Estimate</th><th rowspan="2">t-stat</th><th colspan="3">Marginal effects</th></tr>
<tr><th>Slight Injury</th><th>Serious Injury</th><th>Fatal injury</th><th>Slight Injury</th><th>Serious Injury</th><th>Fatal injury</th></tr>
<tr><td>Model Evaluation</td><td colspan="5"></td><td colspan="5"></td></tr>
<tr><td></td><td colspan="2">OP</td><td colspan="2">HOPIT</td><td>ZIHOPITCD</td><td colspan="2">OP</td><td colspan="2">HOPIT</td><td>ZIHOPITCD</td></tr>
<tr><td>Number of observations</td><td colspan="2">429</td><td colspan="2">429</td><td>429</td><td colspan="2">249</td><td colspan="2">249</td><td>249</td></tr>
<tr><td>Number of estimable parameters (K)</td><td colspan="2">10</td><td colspan="2">14</td><td>19</td><td colspan="2">5</td><td colspan="2">6</td><td>9</td></tr>
<tr><td>Restricted log-likelihood, $LL(0)$</td><td colspan="2">-336.746</td><td colspan="2">-336.746</td><td>-336.746</td><td colspan="2">-148.436</td><td colspan="2">-148.436</td><td>-148.436</td></tr>
<tr><td>Log-likelihood at convergence, $LL(\boldsymbol{\beta})$</td><td colspan="2">-311.723</td><td colspan="2">-300.957</td><td>-284.062</td><td colspan="2">-142.129</td><td colspan="2">-135.955</td><td>-130.947</td></tr>
<tr><td>AIC [AIC=2K-2$LL(\boldsymbol{\beta})$]</td><td colspan="2">643.446</td><td colspan="2">629.914</td><td>606.124</td><td colspan="2">294.258</td><td colspan="2">283.91</td><td>279.894</td></tr>
<tr><td>BIC [$BIC = -2LL(\boldsymbol{\beta}) + K\ln(N)$]</td><td colspan="2">684.0606</td><td colspan="2">686.7744</td><td>683.2917</td><td colspan="2">311.8453</td><td colspan="2">305.0147***</td><td>311.5511***</td></tr>
<tr><td>Vuong test statistic</td><td colspan="5"></td><td colspan="5"></td></tr>
<tr><td>ZIOPITCD vs OP</td><td colspan="5">-3.545</td><td colspan="5">-2.280</td></tr>
<tr><td>ZIOPITCD vs HOPIT</td><td colspan="5">-2.844</td><td colspan="5">-2.084</td></tr>
</table>

OP: Ordered Probit; HOPIT: Hierarchical Ordered Probit; ZIHOPITCD: Zero-inflated hierarchical ordered probit with correlated disturbances

*** To further compare the statistical performance of the hierarchical ordered probit (HOPIT) and the zero-inflated hierarchical ordered probit model with correlated disturbances (ZIHOPITCD), the corrected AIC [$AIC_C = AIC + 2K(K+1)/(N\text{-}K\text{-}1)$] was also calculated. Corrected AIC can account for the impact of estimable parameters as it penalizes models with higher number of estimable parameters (Anastasopoulos, 2016; Fountas and Anastasopoulos, 2018). Corrected AIC for HOPIT model is equal to 284.2571, while corrected AIC for the ZIHOPITCD model is equal to 280.6471; the lower value of the corrected AIC for the ZIHOPITCD model indicates its better statistical performance relative to the HOPIT model.

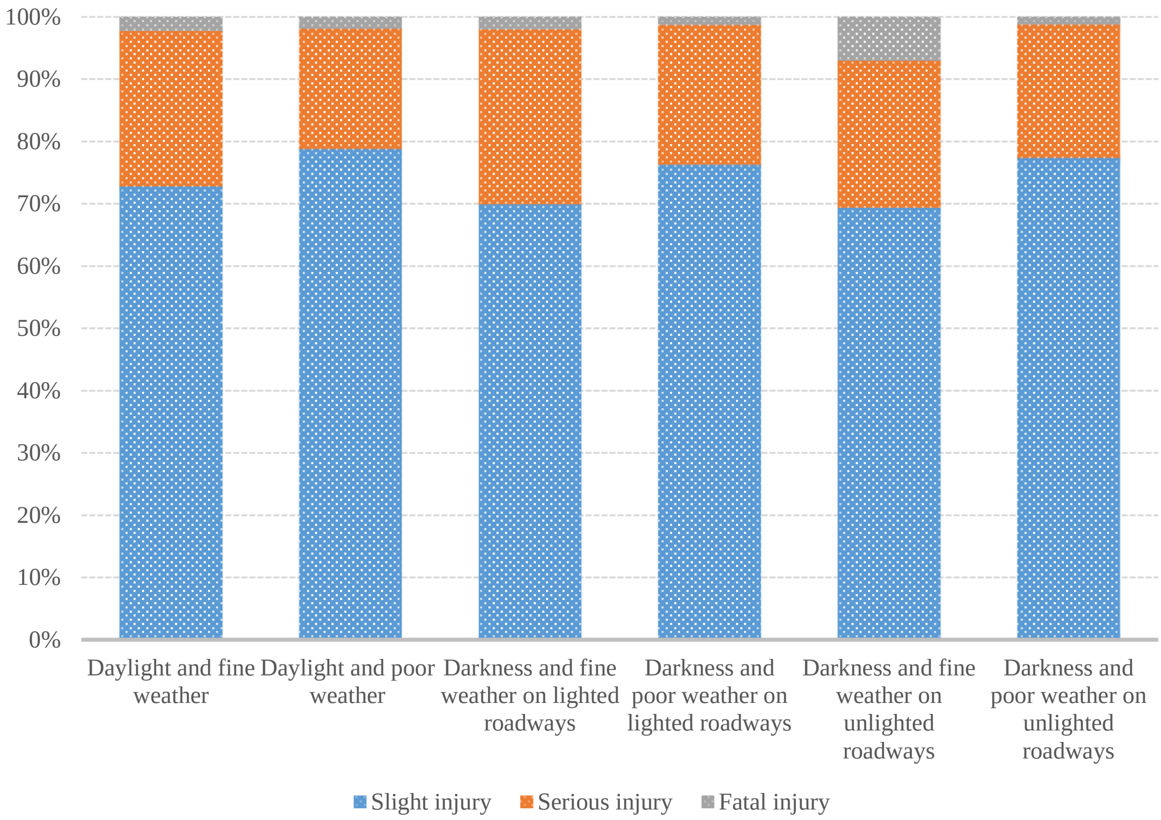

Figure 1. Histograms of accident injury severities for various weather and lighting combinations