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Detecting unforgiving roadside contributors through the severity analysis of ran-off-road crashes

Carlos Roque [a,*], Filipe Moura [b], João Lourenço Cardoso [a]

[a] Laboratório Nacional de Engenharia Civil, Departamento de Transportes, Núcleo de Planeamento, Tráfego e Segurança, Av do Brasil 101, 1700-066 Lisboa, Portugal
[b] CESUR/DECIVIL, Instituto Superior Técnico, Universidade de Lisboa, Av. Rovisco Pais, 1049-001 Lisboa, Portugal

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ABSTRACT

The objective of this paper is to study the contributors influencing ran-off-road (ROR) crash severities in a setting that has not been analysed in the literature, namely on freeways not designed according to the "*forgiving roadside*" concept. To accomplish the analysis, ROR crash data were collected on freeway road sections in Portugal and multinomial and mixed logit models were estimated using the driver injury and the most severely injured occupant as outcome variables. Our results are in line with previous findings reported in the literature on ROR crash severity in a number of distinct settings. Most importantly, this study shows the contribution of critical slopes and vehicle rollover towards fatal injuries and highlights the importance of introducing the "*forgiving roadside*" concept to mitigate ROR crash severity in Portuguese freeways. The study also indicates the importance of protecting errant vehicles particularly in horizontal curves, as these are linked with fatalities. Finally, the empirical findings from the developed models revealed problems in current Portuguese roadside design, especially with regards to criteria for forgiving slopes provision and warrants for safety barrier installation.

1. Introduction

Highway crash injuries are a major burden on modern societies throughout the world. Single-vehicle crashes accounted for 32% of the total number of registered crash fatalities in the European Union during the period 2001–2010 (ERSO, 2012), and single-vehicle off-roadway crashes were linked to 42% of the total fatalities registered in the American FARS in the period 2010–2012 (NHTSA, 2014). In Portugal, single-vehicle ran-off-road (ROR) crashes result in ten thousand crashes with roadside features every year and account for approximately half of all freeway fatalities. Portuguese crash data (2007–2010) indicate that roadside geometry – including slopes, embankments, and ditches – contributes to more than half of all ROR accidents involving serious injury or death (Roque and Cardoso, 2012).

Safety in ROR crashes can be improved by having knowledge of the underlying factors involved in ROR crash occurrences and resulting injuries, so as to develop sound methods to support road design and efficient road operation decision making. The knowledge on ROR crashes on Portuguese roads was recently increased by a roadside safety research project (called SAFESIDE) carried out by the Laboratório Nacional de Engenharia Civil (Roque and Cardoso, 2013). SAFESIDE aimed at developing a procedure for supporting cost-effective decisions with regard to roadside safety benefits, based on cost–benefit analysis (CBA) and statistical methods, to be used in roadside design and redesign. In the US, where the concept of roadside clear zones has been in use since the early 1970s to increase the likelihood that a roadway departure results in a safe recovery rather than a crash (Donnell and Mason, 2006), a cost effectiveness analysis procedure – the Roadside Safety Analysis Program (RSAP) – is currently used for assessing roadside safety improvements (Ray et al., 2012).

Using data based on detailed accident information, the decisive factors in ROR crash frequency and severity can be analysed using statistical methods. A number of ROR crash prediction models exist in road safety literature: for instance, Lee and Mannering (2002), Geedipally and Lord (2010) and Roque and Cardoso (2014) all used Poisson and Negative Binomial regression models to develop ROR crash prediction models. However, the factors that influence accident frequency may differ from those that affect crash severity. For this reason, it is reasonable to analyse the two separately (Savolainen et al., 2011).

A comprehensive and systematic review of the road safety literature shows that no analysis of crash severity on Portuguese

* Corresponding author. Tel.: +351 218 443 970.
E-mail address: croque@lnec.pt (C. Roque).

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roads has been carried out thus far. Furthermore, whilst international literature on the severity of ROR crashes is not scarce, only five studies were identified that specifically addressed the modelling of the effect that roadside conditions have on ROR crash severity.

Lee and Mannering (2002) defined guidelines for identifying cost-effective countermeasures that would improve US highway designs by reducing the severity of crashes involving vehicles leaving the roadway. Indeed, ROR crash severity is a complex interaction of roadside features, such as the presence of guardrails, miscellaneous fixed objects, sign supports, trees and utility poles along the roadway. They noted: "*Some of these roadside features contribute to severity as the result of vehicle–object impact whereas others appear to mitigate severity, presumably by altering driver behaviour (e.g. speed, awareness) in the roadway section*" (Lee and Mannering, 2002).

Holdridge et al. (2005) analysed the in-service performance of roadside hardware in urban areas along the Washington State Route system by developing multivariate nested logit models of injury severity in fixed-object crashes. The study shows the contribution of safety barrier terminals to fatal injuries, and highlights the importance of using well-designed leading ends, as well as the need to upgrade substandard safety barrier terminals on bridges and near other dangerous obstacles. The study also points out the importance of protecting vehicles from crashes with rigid poles and tree stumps, as these objects are linked to greater injury severity and fatalities.

A study conducted by Schneider et al. (2009) shows that ROR crashes resulting in collisions with dangerous roadside objects increase injury severity significantly. Trees were found to be the cause of the greatest increase in incapacitating and fatal injuries. The study concludes that introducing geometric design improvements on curves along rural two-lane highways can help to mitigate the effects of curvature and collisions with roadside objects.

More recently, Xie et al. (2012) analysed injury severity in single-vehicle crashes on rural roads, utilizing a latent class logit (LCL) model. Key injury severity impact factors were identified for rural ROR crashes, including trees, utility poles and concrete barriers.

Finally, Wu et al. (2014) developed mixed logit models to analyse driver injury severity in single-vehicle and multi-vehicle crashes on rural two-lane highways. For single-vehicle crashes with fixed objects, they concluded that the likelihood of being severely injured increased for almost a quarter of drivers involved in such crashes on rural two-lane highways, whereas for a large majority of drivers in other crashes, the likelihood of severe injury decreased. This result indicates the non-uniform effect of fixed roadside objects on driver injury severity and the need for further investigation to analyse the impacts of different types of fixed objects on driver injury outcomes with a view to developing effective countermeasures.

Furthermore, some researchers have documented statistical models that include factors associated with median crash severity in the model specification. Hu and Donnell (2010) found that collisions with cable median barriers tend to result in less severe injuries than collisions with concrete or guardrail median barriers. The study also indicates that increasing the median barrier offset decreases the probability of severe crash outcomes.

Another study conducted by Hu and Donnell (2011) shows that flatter cross-slopes and narrower medians are associated with more severe cross-median crash outcomes, and steeper cross-slopes and narrower medians considerably increase rollover crash severity outcomes. The presence of horizontal curves was associated with increased probabilities of high-severity outcomes in a median rollover crash.

A more recent study on inter-city motorways in France shows that concrete barriers are less effective than W-beam guardrails in reducing cross-median crashes (Martin et al., 2013).

Finally, the NCHRP project 17-44 (2014) conducted research into the factors that contribute to median-related crashes with a view to identifying design treatments and countermeasures that can be applied to improve median safety on divided highways. The research confirms the importance of the traditional approach to improving median safety, which involves design improvements to reduce the consequences of median encroachments (e.g. removing, relocating, or using breakaway design for fixed objects in medians). According to NCHRP project 17-44 (2014), median safety can also be improved by design treatments and countermeasures to make it less likely that motorists will run off the roadway into the median (e.g. providing wider median shoulders).

Roadside design consists in defining the characteristics of the area between the carriageway edges and roadway right-of-way limits and is an important component of the road design process. Concern with roadside characteristics and their influence in road safety is not new. In the US the "*forgiving roadside*" concept has been in use since the 1960s. The studies described above were all carried out in countries where this concept has already been adopted. However, in Portugal, the approval process is still ongoing for new Portuguese roadside design guidelines that integrate this concept within the scope of benefit–cost analysis decision-making (Roque and Cardoso, 2011).

Important data and methodological concerns have been identified in the crash-severity literature over the years as potential sources of error in statistical model specification. They may lead to erroneous crash-severity explanations or predictions, as argued by Savolainen et al. (2011). Omitted-variable bias, endogeneity and underreporting of crashes are examples of those issues. To deal with these data-related problems, state-of-the-art methodological approaches have been incorporated in the statistical methods employed by researchers in an attempt to improve their statistical validity and robustness. However, it is important to keep in mind that these models are intrinsically case specific because they are limited and constrained by the available data, which may be improved over time.

Several researchers have investigated the severity of crashes by considering the injury severity of the driver (Kockelman and Kweon, 2002; Ulfarsson and Mannering, 2004; Wu et al., 2014), whilst others have considered the injury severity of the most severely injured vehicle occupant (Chang and Mannering, 1999; Yamamoto and Shankar, 2004). In this paper we use and compare both. Accordingly, two outcome variables are used: the severity of the injury of the most severely injured occupant (the MSIO models); and the injury severity of the driver of the errant vehicle (the DI models). In both cases, four classes of injury severity are considered: fatal injury, severe injury, minor injury, and no injury – i.e. property damage only (PDO). Detailed information on roadside features and PDO crashes are obtained from a different database and matched to our accident data.

The objective of this paper is to study the factors influencing ROR crash severity in a setting that has not been looked at in the literature, namely on freeways that were not designed in line with the "*forgiving roadside*" concept. Both left-side and right-side carriageway departures are considered, as very few Portuguese dual carriageway medians can be crossed by errant vehicles, thus effectively ruling out frontal collisions between vehicles travelling in opposite directions.

This made it possible to have analysing factors in common with those found in similar studies, whilst also keeping alternative factors within the scope of the study. Accordingly, our modelling approach is mainly explanatory (based on past observations) rather than predictive (predicting new values for the future).

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Additionally, we use multinomial and mixed logit models, which are statistical techniques found, respectively, in Schneider et al. (2009) and Wu et al. (2014), but differ from the nested logit models (Lee and Mannering, 2002; Holdridge et al., 2005) and the LCL model (Xie et al., 2012) also found in the literature for ROR crashes. The inclusion of the mixed logit models allows relaxing the homogeneity assumption of fixed models and thus add a probabilistic dimension to the coefficient analysis. This said, using two outcome variables and two methodological approaches makes this task more comprehensive, reaching different conclusions in the end, desirably. In the final section we discuss measures to be taken into consideration in supporting decisions on roadside safety design in Portugal on the basis of our empirical findings.

2. Methodology

This section describes the methodological approach and techniques applied to analysing injury severity data in this research. A variety of methodological techniques was applied in studying the crash severity data. Savolainen et al. (2011) and Mannering and Bhat (2014) extensively reviewed these methodological alternatives. The most common options in the literature when studying crash severity injuries can be grouped into unordered framework models (including multinomial logit (MNL), nested logit, probit and mixed logit models, among others) and ordered framework models (like ordered probit or logit models and, more recently, generalized ordered models). Overall, researchers' option for one method or another depends mostly on the nature of the dependent variable and differing methodological issues associated with the data.

Selection of the appropriate model for analysing ordinal discrete variables has generated considerable debate. This was recognized by Eluru (2013) and Yasmin and Eluru (2013), who recently have compared the performance of both categories of framework models. The main conclusion is that the generalized ordered logit (GOL) model emerges as the true ordered equivalent when compared to the unordered MNL model for examining ordinal discrete variables. In fact, some shortcomings of traditional ordered models were surpassed with the GOL model.

One of such shortcomings is data underreporting. As mentioned in the previous section, the dependent variables (either for driver injury or most severely injured vehicle occupant) related to multiple response outcomes includes underreporting, especially in relation to PDO crashes. We note that there is no information as to the extent or degree of the underreporting. Furthermore, underreporting of Portuguese crashes can be explained by the lack of reporting by individuals involved in crashes that result in minor or no injury (see Savolainen et al., 2011). Finally, incomplete reporting of crash data is still a significant problem in Portuguese highway safety analysis.

According to Savolainen et al. (2011), traditional ordered probability models are particularly susceptible to the underreporting of crash injury data, while unordered framework models are not afflicted by some of those restrictions (Savolainen et al., 2011; Manner and Wunsch-Ziegler, 2013). As referred above, Eluru (2013) demonstrated that it is possible to address this limitation with GOL model framework. The study concludes that the corresponding performance in the presence of underreporting is likely to be very similar to the MNL.

Another shortcoming of traditional ordered framework models vis-à-vis unordered models is that the former can restrict the influence of explanatory variables on severity outcomes (see Khorashadi et al., 2005 or Yasmin and Eluru, 2013), causing those factors to either increase the probability of greater severity or to increase the probability of lesser severity. Eluru et al. (2008) propose a mixed generalised ordered response logit model (MGORL) structure in order to overcome such restriction and to allow the thresholds in the standard ordered response logit (ORL) model to vary based on both observed as well as unobserved characteristics. Furthermore, the random parameters of both attributes and thresholds can vary across crashes of different individuals due to both observed and unobserved factors.

Finally, Eluru (2013) found that distinct aggregate shares provide variation in model preference clearly highlighting that the aggregate share has an influence on how the alternative model frameworks perform. The same author concluded that the MNL model outperforms (though to a small extent) other model frameworks in aggregate samples that are left skewed, i.e. where less severe injury are more represented than more severe injury or fatality (which is the case of the present data).

All in all, there are many strengths and weaknesses for the ordered framework vis-à-vis the unordered framework (Eluru, 2013), and vice-versa. Given the nature of discrete outcomes of the present data, both ordered and unordered framework models are adequate. By choosing unordered models we opted to disregard the ordered nature of the outcome data and favoured the more common unordered discrete outcome model approach.

The freeware BIOGEME software (Bierlaire, 2003) was used for model estimation, taking advantage of its versatility in specifying the models formulated for this analysis.

2.1. Multinomial logit models

MNL models are traditional discrete outcome models that consider, in this case, four outcomes and do not explicitly consider the ordering that may be present in these outcomes.

The framework used to model the degree of injury severity of a crash-involved individual begins with the definition of a linear function, T, that determines the specific injury severity level j for observation i as (Washington et al., 2011):

$$T_{ij} = \beta_j X_{ij} + \varepsilon_{ij}, \quad (1)$$

where β_j is a vector of coefficients to be estimated for outcome j, X_{ij} is a vector of exogenous (or explanatory) variables, and ε_{ij} is the random component assumed to follow a Gumbel type 1 distribution.

Thus, the probability (P_{ij}) of a driver (or most severely injured occupant) i sustaining a specific injury severity level j is expressed as follows (Washington et al., 2011):

$$P_{ij} = \frac{\mathrm{EXP}\left[\beta_j X_{ij}\right]}{\sum_j \mathrm{EXP}\left[\beta_j X_{ij}\right]}, \quad (2)$$

The MNL model in Eq. (2) requires the assumption that the unobserved terms (ε_{ij}) are independent of the injury severity level – the independence of irrelevant alternatives (IIA) property. Violation of this assumption can lead to serious specification problems. If some injury severity levels share unobserved terms and thus are correlated, the logit formulation will erroneously estimate the coefficient vector and severity probabilities (Shankar et al., 1996). According to Savolainen et al. (2011), empirical studies have shown that the violation of IIA property is very much data dependent: sometimes the property holds, and other times it does not.

A formal test was conducted to ensure the MNL specification is appropriate. The Hausman and McFadden (1984) IIA specification test holds with both final MNL specifications (driver injury, and most severely injured occupant – DI and MSIO models, respectively), which are shown in Fig. 1 and generally expressed by Eq. (2). This structure is used for all MNL and mixed logit models.

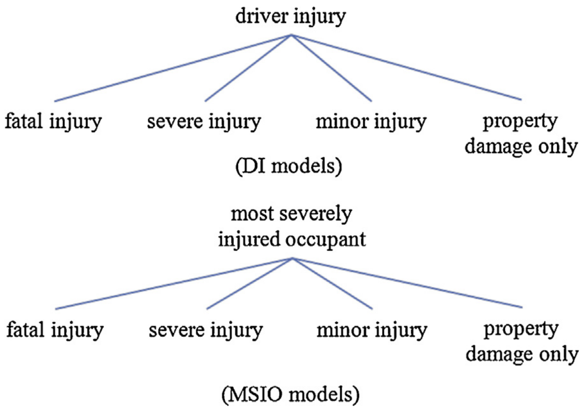

Fig. 1. The MNL and mixed logit structure of the injury severity models.

It is generally acknowledged that the lower injury severity crashes are more likely to be underreported (Yamamoto et al., 2008). Moreover, it is rarely the case that the extent of underreporting is accurately determined, especially in relation to the PDO and crashes resulting in minor injuries (Derricks and Mak, 2007; Patil et al., 2012). Given such underreporting, the observed distribution of reported crashes by injury severity category will differ from the real distribution by severity category. Ignoring underreporting in these models can lead to erroneous inferences. In such a case, and if the IIA property holds, MNL models have the advantage of correctly calculating all estimable parameters, with the exception of the alternative specific constant (Washington et al., 2011).

2.2. Mixed logit models

The mixed logit model was first introduced into transportation research in 1980 (Boyd and Mellman, 1980; Cardell and Dunbar, 1980). Mixed logit models have been applied since then to overcome inefficiencies of the MNL models by allowing for heterogeneous effects and correlation in unobserved factors.

A mixed logit model is derived from MNL by allowing β_j to be random across i individuals in the severity function (Train, 2009):

$$T_{ij} = \beta_{ij} X_{ij} + \varepsilon_{ij} \text{ with } \beta_i \sim f(\beta|\theta), \tag{3}$$

where θ are the parameters of the distribution of β_{ij} over the population, such as the mean and variance of β_{ij}, ε_{ij} is the error term that is independent and identically distributed (iid extreme value property), and does not depend on underlying parameters or data characteristics, and all other variables are as previously defined in Eq. (1).

As mentioned, the mixed logit is a generalisation of the multinomial structure that allows the parameter vector β_j to vary across each driver or most severely injured occupant. The injury outcome-specific constants and each element of β_j may be either fixed or randomly distributed over all parameters with fixed means, allowing for heterogeneity in effects. A mixing distribution is introduced to the model formulation, resulting in injury severity probabilities as follows (Train, 2009):

$$P_{ij} = \int_x \frac{e^{\beta_i X_{ij}}}{\sum_x e^{\beta_i X_{ix}}} f(\beta|\phi) d\beta \tag{4}$$

where $f(\beta|\phi)$ is a density function of β and ϕ is a vector of parameters which describe the density function, with all other terms as previously defined (Milton et al., 2008). The injury severity outcome probability is then simply a mixture of logits (Train, 2009). The distribution is flexible in that β can also be fixed, and when all parameters are fixed the model reduces to the standard MNL formulation. In those instances where β is allowed to vary, the model is in the open form and the probability of an observation having a particular outcome can be calculated through integration (Savolainen et al., 2011).

In this particular case, the parameters vary across the roadway segment population according to a normal distribution (less well-fitting distributions considered but discarded, such as the log-normal and uniform). Estimation can be done by solving the integral with Monte Carlo simulation. Efficiency has been increased using simulation with Halton draws (Halton, 1960), a popular and efficient estimation technique for random parameters models (Bhat, 2003; Train, 2009; Chen and Tarko, 2014).

As mentioned above, in the case of an underreported decision (response) variable, the MNL model provides estimates that are unbiased, i.e. the elasticity effects of the variables are not affected by the underreported data. This advantage applies only to MNL models provided that the dataset under examination satisfies the IIA property, which is the case for our data set. Hence, the mixed logit, by relaxing the IIA property, is unlikely to yield unbiased estimates in the event of underreporting (Yasmin and Eluru, 2013).

2.3. Elasticities

With regard to interpretation of the model, it is known that the estimated coefficients are not sufficient for exploring how changes in the explanatory variables affect the outcome probabilities. The reason for this is that the marginal effect of a variable depends on all the coefficients in the model, so the actual net effect cannot readily be determined from just the value or sign of any single coefficient (Khorashadi et al., 2005).

To assess the vector of estimated coefficients (β_j), elasticities are calculated, which measure the magnitude of the impact of specific variables on the injury outcome probabilities. The elasticity of parameter estimates for continuous regressors is computed for each driver (or most severely injured occupant) i as (Washington et al., 2011):

$$E_{x_{ik}}^{P_{ij}} = [1 - P_{ij}] \beta_j X_{kj}, \tag{5}$$

where P_{ij} is the probability of outcome j and X_{kj} is the value of variable k for specific injury severity level j.

Elasticities are not applicable to dummy variables, however, in these cases, the pseudo-elasticity, $E_{x_{ik}}^{P_{ij}}$, of the kth variable from the vector X_i, denoted X_{ik}, with respect to the probability, P_{ij}, of a person (i) experiencing outcome j can be computed by the following equation (Ulfarsson and Mannering, 2004):

$$E_{x_{ik}}^{P_{ij}} = \left[e^{\beta_{jk}} \frac{\sum_{j'=1}^{J} e^{\beta'_j X_i}}{\sum_{j'=1}^{J} e^{\Delta(\beta'_j X_i)}} - 1 \right] \times 100, \tag{6}$$

where J is the number of possible outcomes, $\Delta(\beta'_j X_i)$ is the value of the function determining the outcome, T_{ij}, after X_{ik} has been changed from zero to one, whereas $\beta'_j X_i$ is the value when $X_{ik} = 0$, X_i is a vector of k explanatory variables shared by all outcomes, β_j is a vector of estimated coefficients on the k variables for outcome j, and β_{jk} is the coefficient on X_{ik} in outcome j.

Elasticities may be either calculated as the average value of the regressors or presented as an average of the elasticities over the sample (Manner and Wunsch-Ziegler, 2013). In this case, average elasticities were used since it is not reasonable to use the average value of dummy variables.

The elasticity value for a variable X_{ik} can be roughly interpreted as the percent effect that a 1% change in X_{ik} has on the injury severity outcome probability P_{ij}. The pseudo-elasticity of a dummy

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variable with respect to a ROR injury severity category represents the percent change in the probability of that injury severity category when the variable is changed from zero to one. Thus, a pseudo-elasticity of 95% for a variable in the PDO category means that when the values of the variable in the subset of observations where $X_{ik}=0$ are changed from 0 to 1, the probability of a PDO outcome for these observations increases, on average, by 95% (Savolainen and Mannering, 2007).

2.4. Goodness-of-fit statistics

Likelihood ratio (LR) tests were used to compare the models, and select the preferred one. The LR test statistic is computed as:

$$\chi^2 = -2[\mathrm{LL_U} - \mathrm{LL_R}], \tag{7}$$

where $\mathrm{LL_U}$ and $\mathrm{LL_R}$ are the log-likelihood of the unrestricted and the restricted models, respectively. The computed value of the LR test is compared with the χ^2 value for the corresponding degrees of freedom (dof). By comparing the improvement in likelihoods as individual variables are added, this test is an efficient way of testing for the significance of individual variables (Washington et al., 2011).

Furthermore, the McFadden adjusted-ρ^2 statistic was chosen from many other ρ^2 proposals (Washington et al., 2011) to measure the explanatory power of the models fitted based on our sample data, according to Eq. (8) (Hensher et al., 2005):

$$\text{adjusted}-\rho^2 = 1 - \frac{\mathrm{LL}^* - p}{\mathrm{LL}^0} \tag{8}$$

where LL^0 and LL^* are the log likelihood of the base (i.e. all β parameters are 0) and the estimated models, respectively; and p is the number of parameters used in the estimated model – thus, accounting for model parsimony and avoiding over-fitting.

Complementary to this, Bayesian information criterion (BIC) was calculated to judge between model explanatory power and parsimony, by accounting for the degrees of freedom (dof) used when comparing the goodness-of-fit (GoF) of different model specifications, according to the following equation:

$$\mathrm{BIC} = -2\ \ln(\mathrm{LL}) - p\ \ln(n) \tag{9}$$

where LL is the log-likelihood of the fitted model, p is the number of parameters used in the model and n is the sample size.

BIC was used instead of Akaike Information Criterion (AIC), as the former is more appropriate for measuring GoF for explanatory power, whilst AIC is more appropriate for measuring predictive accuracy (Shmueli, 2010) and hence for predictive power.

3. Data description

This section describes the characteristics of the freeway dataset. Data characteristics and summary statistics for the ROR injury crash data are presented, as well.

3.1. Data source

In Portugal, injury crash severities are registered by the police and categorised as a function of the victims' stay in hospital and outcome:

- A minor injury is registered when a victim requires hospital treatment but stays there for less than 24 h;
- A severe injury refers to a victim who is registered as a hospital in-patient and stays there for more than a day; and
- A fatality means a victim who dies as a consequence of crash injuries within 30 days of occurrence of the crash.

Portuguese crash data structure allows for categorising ROR accidents by driver injury severity and by the severity of the most seriously injured occupant. Data was provided by the Guarda Nacional Republicana (GNR), which is a police force responsible for maintaining security and public order as well as protecting and defending the population and their property. The GNR is also responsible for road crash investigation and data collection. Whenever an accident occurs GNR officers compile an accident report that includes detailed information such as the injury severity of each vehicle occupant, driver characteristics, factors leading to the accident, weather conditions, and a sketch of the accident scene. Police-reported data also include information that may be used as explanatory variables in modelling injury severity outcomes, including e.g. date, time of day, age and gender of driver, road surface characteristics and conditions, weather conditions, roadway type, speed limits, basic roadway geometrics and type of crash. For accidents involving injury, key information is collected in a statistical bulletin and transmitted to the National Road Safety Authority (ANSR), which manages the Portuguese road accidents database, a main source of evidence for this study. However, information on roadside features is incomplete. It was thus necessary to collect additional information from the original accident reports, which are only available on paper. The accident scene sketch and the crash description made it possible, in most cases, to identify the carriageway departure side and the roadside features hit by errant vehicles. A few PDO crashes were also added to the ANSR database, as the original GNR accident reports include all injury crash severity levels.

3.2. Sample formation and description

The main focus of this study is on driver injury severity and on the most severely injured occupants of errant vehicles in ROR crashes. The following criteria were employed for sample formation:

- Crashes that involved only one vehicle were selected;
- ROR crashes that occurred on freeways basic segments were examined; and
- ROR crashes reported at interchange ramps (or within a 250 m radius) and weaving areas were excluded from the analysis. Whenever the accident scene sketch included an interchange ramp or a weaving area, the ROR crash was excluded from the sample, even when the accident was located up or downstream of those roadway components, in order to make sure that they were not within corresponding influence areas.

A total of 765 crashes were selected, out of 840 registered ROR crashes on dual carriageway roads.

Only single-vehicle ROR crashes involving roadside features were used in this study. Roadside features include impact attenuators, bridge parapet ends, bridge rails, guardrail fences, guardrail ends, median barriers, highway traffic sign posts, overhead sign supports, utility poles, culverts, curbs, ditches, embankments, trees, and other fixed objects. Multi-vehicle crashes were excluded.

ROR crashes with missing information on the accident, driver or vehicle characteristics were removed before the statistical analysis, which resulted in a final data set of 764 ROR crashes that occurred on Portuguese freeways during the years 2009 and 2010. The severity of the accidents falls into the same categories referred to above – fatal, severe injury, minor injury and PDO. This dataset comprises 580 km of dual carriageway freeway segments situated in various regions across Portugal. All segments have full access control, two lanes per carriageway and paved shoulders (with widths of less than 2.5 m and 4.0 m for left and right shoulders,

Table 1
Descriptive statistics of ROR crash severity.

Outcome variable	Fatal	Severe injury	Minor injury	PDO	Total
Driver injury					
Number of occurrences	6	47	586	125	764
Percentage	0.8%	6.1%	76.7%	16.4%	100%
Most severely injured occupant					
Number of occurrences	8	67	677	13	765
Percentage	1.0%	8.8%	88.5%	1.7%	100%

respectively). Access to and from the freeway is only possible through interchange ramps.

Table 1 shows the distribution of the accidents by injury category for the two variables of interest considered. Only 0.8% of all accidents involving the driver were fatal (1.0% considering the most severely injured), while a large majority of crashes were minor injuries. Of the 764 ROR crashes reported, 125 (16.4%) resulted in no injury for the driver. In one case, the driver's injury severity is unknown. Most crashes involved injuries to at least one occupant; this results from the data source, as the ANSR database only contains injury crashes and the police seldom makes an accident scene sketch for PDO crashes when vehicles are moved from the resting positions before official reporting.

The datasets contain information on a number of attributes related to the ROR crashes. Those that proved to be relevant for explaining crash severities are listed in Tables 2 and 3, depending on whether they are categorical or continuous variables, respectively. In the case of Table 2, the proportion of observations of values 1 or 0 for dummy variables is presented, whereas in the case of continuous variables the mean and standard deviation parameters are included.

The afternoon peak was considered but was not significant for all the models and categories included in the analysis. One possible reason for this could be the fact that the afternoon peak hour is much less concentrated and therefore no strong peaking occurs. The variables age and female refer to the errant vehicle driver; thus it may differ from the most severely injured occupant. This makes the interpretation of the effects of these variables difficult in MSIO models. Indeed, in some crashes the person responsible is the most severely injured victim and in others that is not the case. Comparing the two sets of the same database, sorted for each outcome variable, we observe that there is a major shift from PDO crashes (from 16.4% to 1.7% of cases) to more severe or fatal injuries, but predominantly minor injuries (from 76.7% to 88.5% of cases). Although referring to the same database, choosing different outcome variables has an impact on the modelling outcomes. It is important to bear this in mind when interpreting the corresponding effects in these models and, therefore, on the conclusions reached at the outset.

4. Modelling results

This section describes the results of the comparative analysis between the two outcome variables (driver and most severely injured occupant) and the two methodological approaches considered (MNL and mixed logit). As mentioned in Section 2.2, a common way of dealing with potential heterogeneity is to use a mixed logit model, which allows for selected parameters to be randomly distributed. Two mixed logit models were estimated in this study. In order to improve the numerical stability, the number of Halton draws to evaluate the log-likelihood function was 1000.

4.1. Significant variables

In this analysis, a host of variables were selected from five broad categories: seasonal attributes (including night, winter and peak hour), roadside attributes (including collisions with slopes and barriers and the number of obstacles involved), roadway attributes (including encroachment direction, horizontal curves and straight segments), accident information (including speed limit, vehicle

Table 2
Descriptive statistics of the categorical regressors.

Variable category	Variable	Description of dummy variables	% yes ($D=1$)	% no ($D=0$)
Seasonal attributes	Night	Night	32.9	67.1
	Winter	Winter (December, January or February)	29.5	70.5
	Peak hour[a]	Morning period (07.30 to 10.00 am)	13.5	86.5
Roadside attributes	Slope	First harmful event being traversing/colliding with slope	11.8	88.2
	Barrier	First harmful event being collision with metallic safety barrier	41	59
Roadway attributes	Right curve	Horizontal curve to the right	12.3	87.7
	Straight	Straight segment	74.9	25.1
Accident information	Right encroach	Leaving the road to the right side of the carriageway	55.2	44.8
	Rollover	Rollover	36.6	63.4
	Car	Passenger car involved	75.8	24.2
Driver information	Female	Gender (female = 1)	36.9	63.1

[a] Morning peak period definition is informed guessing, based on traffic studies.

Table 3
Descriptive statistics of the continuous regressors.

Variable category	Variable	Description	Mean	sd	Min	Max
Roadside attributes	Obstacles	Number of obstacles[a] hit in a ROR crash	1.508	0.708	0	4
Roadway attributes	Speed limit	Segment speed limit	119.764	2.334	90	120
Accident information	Persons involved	Number of involved persons	1.562	0.855	1	7
Driver information	Age	Driver age, in years	38.282	13.813	18	83

[a] Includes safety barriers.

Table 4
Estimated coefficients of the DI models.

Severity level	Variable coefficient	MNL			Mixed logit		
		Coefficient estimate	*t*-test	*p*-value	Coefficient estimate	*t*-test	*p*-value
Fatal injury	Peak hour	−1.340	−1.83	0.07	−2.820	−1.8	0.07
	Slope	1.760	2.06	0.04	–	–	–
	Straight	−2.310	−2.57	0.01	−2.820	−1.8	0.07
	Rollover	0.778	2.67	0.01	0.791	2.02	0.04
	Persons involved	0.967	8.36	<0.001	2.010	6.88	<0.001
	Std. dev. of parameter (Persons involved)	–	–	–	1.460	4.28	<0.001
Severe injury	Constant (specific to severe/minor injury)	6.530	8.53	<0.001	10.400	6.72	<0.001
	Peak hour	−1.340	−1.83	0.07	−2.370	−1.58	0.11
	Speed limit	−0.029	−9.39	<0.001	−0.035	−7.91	<0.001
	Rollover	0.778	2.67	0.01	0.791	2.02	0.04
Minor injury	Constant (specific to severe/minor injury)	6.530	8.53	<0.001	10.400	6.72	<0.001
	Night	−0.421	−2.11	0.04	−0.479	−1.71	0.09
	Right curve	0.628	1.93	0.05	0.792	1.73	0.08
	Age	−0.016	−2.4	0.02	−0.022	−2.3	0.02
PDO	Constant	2.490	3.41	<0.001	4.190	3.47	<0.001
	Winter	0.600	2.55	0.01	0.817	2.25	0.02
	Barrier	0.369	1.69	0.09	0.497	1.47	0.14
	Right encroach	−0.762	−3.45	<0.001	−0.939	−2.72	0.01
	Car	0.465	1.63	0.10	0.629	1.49	0.14
	Persons involved	0.967	8.36	<0.001	2.010	6.88	<0.001
	Std. dev. of parameter (Persons involved)	–	–	–	1.460	4.28	<0.001
	Female	−0.884	−3.38	<0.001	−0.913	−2.42	0.02
Number of observations			764				764
Log likelihood at zero			−1059.129				−1059.129
Log likelihood at convergence			−463.266				−449.009
Degrees of freedom (dof)			16				16
Adjusted-ρ^2			0.547				0.561
Bayesian information criteria (BIC)			93.940				94.003

Note: constant terms for severe and minor injury are the same as the covariance/correlation analysis of pairs of estimated coefficients where it is indicated that the two parameters are not significantly different and are, thus, treated as generic (Ortuzar and Willumsen, 2011). The attribute persons involved was restricted to be equal across fatal and PDO injury severity levels, the peak hour and rollover attributes were restricted to be equal across fatal and severe injury severity levels.

rollover, vehicle type and number of persons involved) and driver information (including driver gender and age).

Altogether, 57 parameters were calibrated across 4 models, through which we could identify the potential effects of different factors related to the categories listed above. It is important to point out that most parameters were statistically significant with *p*-values below 5% (i.e. confidence levels above 95%), with 13 exceptions where *p*-values ranged between 5% and 10% and 7 cases where *p*-values went up to 15% in separate models. As stated above, in our case the aim was to detect unforgiving roadside contributors through a retrospective severity analysis of ran-off-road crash data and therefore use the models for explanatory purposes (within the range of values observed, only), where lower *p*-values are acceptable (Washington et al., 2011).

Several variables could not be considered in our analysis because either the information was entirely unavailable or there was a large amount of data for these attributes missing in the dataset. This is the case for shoulder and clear zone widths, number of lanes, traffic volumes and lighting condition. Variable time of day was used as a surrogate for lighting conditions.

Only statistically significant explanatory variables were considered in the final specification models. A minimum confidence level of 85% was considered as criterion, which was met by 7 regressors out of 57 in the four calibrated models. In those cases where the variable effects were not significantly different, their coefficients were restricted to be equal. In order to minimise the bias and reduce the variability of the models, fatal injury was set as the baseline severity level for all MNL and mixed logit models (Ye and Lord, 2011); the alternative specific constant (ASC) was defined accordingly.

4.2. Models and interpretation

We begin by reporting the estimation results using the driver injury (DI) and the most severely injured occupant (MSIO) as the outcome variables. The estimated parameters are shown in Tables 4 and 5, respectively.

In the end, the DI and MSIO models have the same specification, except for the inclusion of the slope parameter in the case of the MNL formulation for the DI model. MNL and mixed logit models preserve the signs of the parameters and respective *p*-values remain roughly the same. Sign shifting occurs only between DI and MSIO for the variable persons involved for PDO, as will be discussed in Section 5. Nevertheless, the expected values of the parameters differ between the MNL and mixed logit models, which are mirrored in the differences in respective elasticities (see Tables 6 and 7).

In the DI model, the explanatory variable persons involved has a random coefficient for the categories fatal injury and PDO. In the MSIO model, the explanatory variable speed limit has a random coefficient for the category severe injury. In both cases the estimated standard deviations of the random coefficients are about one half of the estimated coefficients, which indicates that only positive effects are most likely for those variables (the probability of the coefficient to shifting signs is 8% and 1% for persons involved and speed limit, respectively). Their estimated parameters were found to be normally distributed instead of having fixed values across all observations.

Overall, the estimation results of the mixed logit models confirm the qualitative findings from the fixed parameter models. Nevertheless, the mixed logit models resulted in greater log-

Table 5
Estimated coefficients of the MSIO models.

Severity level	Variable coefficient	MNL			Mixed logit		
		Coefficient estimate	*t*-test	*p*-value	Coefficient estimate	*t*-test	*p*-value
Fatal injury	Peak hour	−0.999	−1.85	0.06	−1.980	−1.74	0.08
	Obstacles	0.402	2.54	0.01	0.815	2.53	0.01
	Slope	1.300	1.72	0.09	1.200	1.49	0.14
	Straight	−1.230	−1.69	0.09	−1.340	−1.73	0.08
	Rollover	0.832	3.26	<0.001	1.360	2.62	0.01
Severe injury	Constant (specific to severe/minor injury)	6.480	7.25	<0.001	8.740	5.13	<0.001
	Peak hour	−0.999	−1.85	0.06	−1.980	−1.74	0.08
	Obstacles	0.402	2.54	0.01	0.815	2.53	0.01
	Speed limit	−0.036	−7.94	<0.001	−0.007	−3.4	<0.001
	Std. dev. of parameter (Speed limit)	–	–	–	−0.003	−2.43	0.01
	Rollover	0.832	3.26	<0.001	1.360	2.62	0.01
Minor injury	Constant (specific to severe/minor injury)	6.480	7.25	<0.001	8.740	5.13	<0.001
	Car	0.471	1.78	0.08	0.662	1.7	0.09
	Persons involved	−0.496	−4.02	<0.001	−0.948	−3.19	<0.001
	Age	−0.013	−1.53	0.13	−0.0002	−1.46	0.15
PDO	Constant	2.370	2.74	0.01	4.530	2.82	0.00
	Persons involved	−0.496	−4.02	<0.001	−0.948	−3.19	<0.001
Number of observations			764				764
Log likelihood at zero			−1059.129				−1059.129
Log likelihood at convergence			−307.984				−305.831
Degrees of freedom (dof)			12				13
Adjusted-ρ^2			0.698				0.699
Bayesian information criteria (BIC)			68.203				74.885

Note: constant terms for severe and minor injury are the same as the covariance/correlation analysis of pairs of estimated coefficients where it is indicated that the two parameters are not significantly different and are, thus, treated as generic (Ortuzar and Willumsen, 2011). The attribute persons involved was restricted to be equal across fatal and PDO injury severity levels, the peak hour and rollover attributes were restricted to be equal across fatal and severe injury severity levels.

likelihoods: from −463 to −449 and from −308 to −306 for the models with driver injury and most severely injured occupant as outcome variables, respectively. Accordingly, the forthcoming analysis will be based on the mixed logit calibration results and complemented with additional comments addressing the differences highlighted above.

As mentioned above, the parameter coefficient estimates may be misinterpreted, since a positive coefficient does not necessarily indicate an increase in the likelihood of that particular injury severity level. In order to assess the vector of the estimated parameter coefficients (β_j) properly, parameter-specific elasticities (for continuous variables) and pseudo-elasticities (for categorical variables) are used in Table 6 to measure the impact of individual parameters on the likelihood of the four injury severity outcomes for the DI models. When analysing the effects of continuous variables, the percent variation of crash outcomes is compared with a 10% variation of the stimulus variable (in this case, the factors we are analysing). In the case of categorical variables, since the variation in the stimulus factors (i.e. dummy variables) is necessarily from 0 (the baseline) to 1, then the percent variation of crashes outcomes refers to a variation of 100% in the regressors.

During peak hours ROR crashes are 91% and 90% less likely to result in a fatal or severe injury, respectively, when compared to the baseline of non-peak hour periods. In the case of ROR crashes, physics and logical considerations lead to the conviction that the relationship between expected severity and traffic flow is not a linear one. In low traffic flows one may expect higher travel speeds

Table 6
Pseudo-elasticities for the DI models.

Variable	MNL				Mixed logit			
	Fatal injury	Severe injury	Minor injury	PDO	Fatal injury	Severe injury	Minor injury	PDO
Peak hour	−0.74	−0.72			−0.91	−0.90		
Slope	4.69							
Straight	−0.90				−0.94			
Rollover	1.16	1.07			1.20	1.14		
Persons involved	1.49			1.16	3.03			2.12
Speed limit		−3.27				−4.03		
Night			−0.10				−0.10	
Right curve			0.14				0.20	
Age			−0.15				−0.21	
Winter				0.34				0.94
Barrier				0.36				0.50
Right encroach				−0.47				−0.51
Car				0.49				0.70
Female				−0.53				−0.50

Note: this table reports the elasticities corresponding to the estimation results in Table 4. Elasticities are averaged overall observations. Persons involved, speed limit and age are continuous variables, and their elasticities are computed per Eq. (5). For binary regressors we report the pseudo-elasticities using Eq. (6).

Table 7
Pseudo-elasticities for the MSIO models.

Variable	MNL				Mixed logit			
	Fatal injury	Severe injury	Minor injury	PDO	Fatal injury	Severe injury	Minor injury	PDO
Peak hour	−0.63	−0.61			−0.86	−0.46		
Obstacles	0.60	0.55			1.23	0.25		
Slope	2.63				2.32			
Straight	−0.70				−0.74			
Rollover	1.29	1.14			2.90	0.36		
Speed limit		−3.95				−0.20		
Car			0.06				0.70	
Persons involved			−0.10	−0.77			−1.21	−1.48
Age			−0.06				−0.006	

Note: this table reports the elasticities corresponding to the estimation results in Table 5. Elasticities are averaged over all observations. Speed limit, persons involved and age are continuous variables, and their elasticities are computed per Eq. (5). For binary regressors we report the pseudo-elasticities using Eq. (6).

(and lower densities) than in high traffic flows (with higher densities); therefore, in the event of an impact with a roadside hazard, high levels of kinetic energy dissipation can be expected. As traffic flows increase, travel speeds will decrease and densities will increase accordingly. Hence, for ROR crashes, higher severity levels cannot be expected to occur at higher flows. When traffic is congested, space headway between vehicles is smaller, and hence ROR crashes are unlikely, except when the departure angle is large or in very low skid resistance conditions, such as ice and snow covered pavements.

ROR crashes involving slopes increase the risk of fatality for the driver by 469%, when compared to the baseline situation of not facing slopes. This result could, at least, be partially expected, as slopes steeper than 3H:1V (where there is a 1 m height increase for every 3 m horizontal length) are frequently used on Portuguese freeways. These slopes are in fact a non-traversable area for errant vehicles that leave the roadway and encroach into the roadside.

The variable straight refers to cases where ROR crashes occur within a straight segment in contrast to those that occur in curved segments. The negative parameter (−2.82) specific to fatal outcomes and its corresponding (pseudo-) elasticity of −0.94, show that tangents have a lower likelihood of drivers being fatally injured by 94%. As expected from earlier findings in the literature and from intuition, vehicle rollover increases the driver's risk of fatality or severe injury by 120% and 114%, respectively, in comparison to non-rollover crashes. We also see that increasing the number of persons involved (which is a continuous variable) by 10% increases the risk of driver's fatality or PDO by 30.3% and 21.2%, respectively. This is an issue that merits further analysis, based on an enlarged crash data set. There seems to be two different types of accidents (one resulting in fatalities and the other in no injuries). It will be interesting to break the data down further and investigate if there are age-related dependencies (for instance, due to risky manoeuvres by young drivers under peer pressure from fellow occupants; or due to leisure driving by middle aged drivers travelling with relatives and co-workers).

Reducing the speed limit (which is also a continuous variable) by 10% decreases the risk of severe injury by 40.3%, denoting a significant elasticity of severe crashes with respect to speed. This finding was to be expected, as lower speed limits should lead to lower impact speeds with roadside hazards and reduced levels of kinetic energy dissipation in comparison to higher impact speeds. Also, speed limits on Portuguese motorways are mostly applied to urban stretches, where congestion conditions are more frequent than in interurban areas.

Driver minor injury is 10% less likely when ROR crashes occur at night, compared to the other periods of the day. The effect of age on minor injuries is similar, being 2.1% less likely for every 10% increase in age. One can also observe that horizontal alignment (such as if an ROR crash occurred on a right curve) increases the chance of minor injury to the driver by 20%, in comparison to crashes on straight segments or left curves.

The variable winter increases the probability of property damage by 94% in comparison to other seasons of the year. This may be due to the fact that drivers acknowledge the riskiness of winter conditions, thus slowing down, and that available skid resistance is lower and drivers may lose control at lower speeds. In both cases lower departure speeds are expected, making minor ROR crashes more likely.

ROR crashes due to collisions with metal safety barriers also tend to result in PDO more often (50%) in comparison to other types of barriers. This may be due to the fact that a metal safety barrier has a greater capacity of energy absorption than other hazards placed on the roadside of Portuguese freeways, resulting in reduced vehicle occupant decelerations in a collision. The results for right encroach suggest that leaving the carriageway to the right side decreases the chance of PDO (a drop of 51%). Cars are 70% more likely to face PDO crashes than other vehicles types, suggesting that car crashworthiness devices are more effective in ROR crashes than in other vehicle types. The negative coefficient estimate for the female driver indicator suggests that female drivers have a

Table 8
Summary of qualitative findings.

Severity level	Variable	Driver injury	Most severely injured occupant	Overall effect
Fatal injury	Peak hour	↓	↓	↓
	Obstacles	–	↑	↑
	Slope	↑	↑	↑
	Straight	↓	↓	↓
	Rollover	↑	↑	↑
	Persons involved	↑	–	↑
Severe injury	Peak hour	↓	↓	↓
	Obstacles	–	↑	↑
	Speed limit	↓	↓	↓
	Rollover	↑	↑	↑
Minor injury	Night	↓	–	↓
	Right curve	↑	–	↑
	Car	–	↑	↑
	Persons involved	–	↓	↓
	Age	↓	↓	↓
PDO	Winter	↑	–	↑
	Barrier	↑	–	↑
	Right encroach	↓	–	↓
	Car	↑	–	↑
	Persons involved	↑	↓	0
	Female	↓	–	↓

Note: this table summarizes the qualitative findings of our study, where "–" means not significant for the relevant model; "↑" means that a factor generally increases the propensity of a ROR for the severity level considered; "↓" means that it generally decreases the propensity; and "0" means that no clear effect could be identified.

lower probability of PDO in a ROR crash when compared to male drivers (less 50%).

Table 7 presents the results when the MSIO is used as the outcome variable. One should first note that the variables night and right curve (for the category minor injury), and winter, barrier and right encroach (for the category PDO) are not significant in this case. The variables persons involved and car, previously significant for the categories fatal injury and PDO, respectively, are now significant for categories minor injury and PDO, indicating that when all vehicle occupants are considered, the less severe crashes are statistically related to the presence of more occupants in the vehicle. Based on these results, when the number of vehicle occupants is higher, ROR crashes are more likely to result in a severe or fatal injury to an occupant. This is to be expected, as there are more persons that may be injured and the occupants are closer to the vehicle frame, other hard objects (e.g. windshields) and other occupants.

Obstacles is a new significant variable for the categories fatal injury and severe injury, associated with a risk of fatality increase of 12.3% and a rise in risk of severe injury of 2.5%, when the number of obstacles faced increases by 10% (as this variable is continuous). Otherwise, the results are similar to those obtained for when the outcome variable selected is driver injury.

5. Discussion

A summary of the qualitative findings is presented in Table 8. As mentioned above, the models – MNL and mixed logit – using the driver injury and the most severely injured occupant as outcome variables, overall, lead to the same conclusions regarding the effects direction influencing ROR crash severity. Only in the case of PDO crashes is there an exception regarding the effect of the number of persons involved. As mentioned in Section 4.2, this may result from the MSIO models being influenced by the higher number of persons at risk and the DI models reflecting different types of travel characteristics and ROR crashes.

Additionally, our results are in line with previous findings reported in the literature on ROR crash severity in a number of distinct settings. This is the case for rollover and speed limit, which were found to increase the propensity for fatal and severe injury ROR crashes, just as in Hu and Donnell (2010), Xie et al. (2012), Wu et al. (2014) for rollover, and Lee and Mannering (2002) for the latter factor. According to Holdridge et al. (2005), driver injuries tend to be PDO in ROR crashes with higher number of persons involved, which partially agrees with our results (where both fatalinjury and PDO have higher propensity scores). The presence of curves is also found to increase the chance of minor injury ROR crashes in our study and in Lee and Mannering (2002).

On the other hand, female drivers were found to have lower probabilities of PDO ROR crashes. This agrees with findings from Xie et al. (2012) and Wu et al. (2014), but differs from the results obtained by Schneider et al. (2009), who found that female drivers are more likely to be injured in ROR crashes.

There are also several factors for which different studies found distinct, but not necessarily incompatible, effects. Some of these are the role of driver age and the involvement of passenger cars in ROR crashes.

Most importantly, our study adds some new findings on the effect that some variables have on ROR crash severities for the case of freeways with "unforgiving" roadsides.

Lee and Mannering (2002)found that the presence of guardrails in the roadway section increased the chance of an accident resulting in a disabling injury/fatality. These conclusions are in line with the forgiving roadside concept where protecting traffic by means of a safety barrier is the traffic engineer's weakest choice regards roadside safety intervention. The underlying requirement is that the safety barrier will result in a collision severity that is lower than a collision with the roadside obstacle being shielded. However, Martin et al. (2013) found that the absence of guardrails in the shoulder contributes to significantly higher injury rates, including when the roadside is essentially at the same level as the roadway.

In our study, higher propensity for PDO ROR crashes is associated with the presence of metal safety barriers. This does not necessarily question the effectiveness of guardrails in protecting traffic from other dangerous obstacles (when compared with other solutions, such as removing obstacles that decrease the probability of obstacles being hit and reduce the potential danger of an obstacle) but may simply reflect problems in the current Portuguese definition of roadside hazard, particular with regard to slopes and embankment slopes. Indeed, our study also shows that traversing a slope tends to increase the chance of a fatal or severe injury ROR crash. In contrast to this, Schneider et al. (2009) found that when drivers strike an embankment, injuries generally tend to be less severe. This apparent contradiction arises from current Portuguese design guidelines that do not treat critical slopes (slopes steeper than 3H:1V) as roadside hazards if their height is less than 3.0 m. Accordingly, safety barriers are not installed on embankment slopes this high, and traffic is not protected from this type of hazard.

Given our empirical findings, as summarized in Table 8, this research provides some direction with regard to countermeasures that improve roadside design by reducing the severity of ROR crashes when errant vehicles leave the carriageway and which deserve to be considered when cost-effective roadside safety interventions are considered in redesigning existing roads or managing their operation.

In terms of roadside treatments, our results show that avoiding critical slopes – particularly on curves – and other roadside layout configurations prone to errant vehicle rollover and providing safety barriers with an adequate length upstream from dangerous obstacles can reduce ROR crash severity significantly. The provision of run-off zones with recoverable slopes (slopes flatter than 4H:1V) in horizontal curves can be a first step toward forgiving roadsides on Portuguese freeways. It is also important to stress the need for improved warrants for safety barrier installation. According to Zou et al. (2014), the safety effects of safety barriers are positive if they are installed properly and are justified by the presence of roadside hazards that would be costly to eliminate.

Finally, comparing the models obtained for different outcome variables – i.e. driver injury (DI) and most severely injured occupant (MSIO) – also provides interesting insights. The explanatory gains when comparing DI and MSIO models are that different sets of attributes are obtained and therefore more unforgiving roadside contributors are detected. Importantly, the overall conclusions are maintained as Table 8 illustrates. These differences occur mainly because the severity distribution varies when the outcome variable changes (refer to Section 3).

6. Summary and final remarks

This paper shows the contribution of critical slopes and vehicle rollover to fatal injuries, and highlights the importance of introducing the "*forgiving roadside*" concept to mitigate ROR crash severity on Portuguese freeways. The study also shows the importance of protecting errant vehicles, particularly in horizontal curves, as these are linked with fatalities.

To carry out the analysis, ROR crash data was collected on sections of freeways in Portugal. Models were then estimated for the two methodological approaches (multinomial and mixed logit models) and two outcome variables considered (the injury severity of errant vehicle drivers and the most severely injured occupant). Elasticities were also computed to complement the analysis.

When we compare the calibration results from the MNL and mixed logit models, we conclude that there are no major changes, except for one attribute: the number of persons involved in the accident. Nevertheless, the goodness of fit of mixed logit was higher both for driver injury (DI) and most severely injured occupant (MSIO) models and, thus, there was a gain in the quality of the models obtained, although to a limit extent. Interestingly, random parameters calibrated for both models allow for a probabilistic interpretation of the attributes number of persons involved and speed limit for the DI and MSIO models, respectively. In both cases, we conclude that the probability of the corresponding coefficients shifting signs (i.e. from positive to negative or vice-versa, respectively) is low (<8%). This suggests that although there are different propensities of severity levels for the crashes analysed herein, they maintain the same type of effect (i.e. either positive or negative) when varying these attributes. Furthermore, by analysing the dataset for the two outcome variables, we gain in explanatory power by detecting more contributors to unforgiving roadside, based on the severity analysis of the ROR crashes analysed.

The empirical findings from the developed models reveal problems in current Portuguese roadside design, especially with regard to criteria for forgiving slopes and warrants for safety barrier installation. This underscores the need for the swift application of the "*forgiving roadside*" concept recommended in the new Portuguese roadside design guidelines (Roque and Cardoso, 2011). Nevertheless, ongoing developments in road asset management and inventory systems are providing additional and enhanced data on roadside characteristics and crashes, thus creating the basis for further research leading to more accurate recommendations as to how to increase roadside safety in the most effective way.

There are some interesting topics to focus on and explore as future work developments, namely the joint analysis of ROR crash frequency and severity, through multivariate models, to accommodate the correlation of unobserved factors among crash counts by severity level. Furthermore, it is important to note that the procedure developed in SAFESIDE (as mentioned above and described in Roque and Cardoso, 2015) does not take into consideration the probability of occurrence of crashes at different severity levels conditioned on crash occurrence. By estimating the probability of crash occurrence at different severity levels, these crash severity models can be integrated in said procedure in order to estimate the expected number of crashes at different severity levels and thus produce improved crash cost calculations. Finally, changes over time of the main contributors to unforgiving roadside can be detected by analysing time series of crash records.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.aap.2015.02.012. These data include GoogleMaps™ pinpoints from segment examples of the dataset described in this article.

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