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Improving roadside design policies for safety enhancement using hazard-based duration modeling

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ABSTRACT

Roadway departure (RwD) crashes, comprising run-off-road (ROR) and cross-median/centerline head-on collisions, are one of the most lethal crash types. Nationwide, from 2014 to 2016, annual RwD crashes accounted for 53% of all motor vehicle traffic fatalities. Several factors may cause a driver leave the travel lane, including an avoidance maneuver and inattention or fatigue. Roadway and roadside geometric design features (e.g., lane widths and clear zones) play a significant role in whether human error results in a crash. In this paper, we present a hazard-based duration model to investigate the distance traveled by an errant vehicle in a run-off-road crash, the stopping hazard rates, and associated risk factors. For this study, we obtained five years' (2010–2014) of crash data related to roadway departures (i.e., overturn and fixed-object crashes) from the Federal Highway Administration's Highway Safety Information System Database. The results indicate that over 50% of the observed vehicles traveled no more than 36 ft. in a ROR crash and 25% of the observed vehicles traveled at least 78 ft. We also found that seasonal, roadway, and crash variables, along with vehicle information and driver characteristics significantly contributed to the distances traveled by errant vehicles in ROR crashes. This paper presents methodological empirical evidence that the Cox proportional-hazards model is appropriate for investigating the distances traveled by errant vehicles in ROR crashes. In addition, it also provides valuable information for traffic design and management agencies to improve roadside design policies and implementing appropriately forgiving roadsides for errant vehicles.

1. Introduction

Roadway departure (RwD) crashes occur when a vehicle departs from the traveled way either by crossing an edge line or a centerline. RwD events comprise both run-off-road (ROR) and cross-median/centerline head-on collisions. These crashes are known for their tendency to be more severe than other crash types and result in more fatalities by virtue of being mostly head-on crashes, opposite-direction sideswipe collisions, and fixed object crashes. According to the Federal Highway Administration (FHWA) Roadway Departure Safety Program, this crash type accounts for the majority (more than 50%) of traffic fatalities in the United States. More specifically, overturns (30%), opposite direction (23%), and trees/shrubs (19%) crashes account for more than 70% of all roadway departure crashes. Given these sobering statistics, developing greater insight into the crash contributing factors and mitigation strategies will be valuable.

There are a number of reasons a driver may leave the travel lane, such as an avoidance maneuver, inattention, or fatigue. Roadway and roadside geometric design features (e.g., lane and shoulder widths, sideslope, fixed-object density, and offset from fixed objects) play a significant role in whether human error will result in a crash.

Only in the late 1960s, roadside safety design (as the design of the area outside the traveled way) became a discussed aspect of highway design, and it was in the decade of the 1970s that this type of design was regularly incorporated into highway projects (AASHTO, 2011). Clear zones were created since the early 1970s to increase the likelihood that a roadway departure results in a safe recovery rather than a crash, and mitigate the severity of crashes that do occur (Donnell and Mason, 2006). Under this philosophy, roadside hazards within the clear zone are either eliminated or moved. When hazards cannot be removed or relocated, a determination needs to be made if a safety device (e.g., using an appropriate breakaway device, guardrail or crash cushion) is warranted to protect occupants from the roadside obstacle. The forgiving roadside concept has guided the development of design policies to the present day, such as the fourth edition of American Association of State Highway and Transportation Officials' Roadside Design Guide

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(RDG) (AASHTO, 2011).

Information collected between the 1960′s and early 80′s in North America are still the main source of roadside encroachment data (Hutchinson and Kennedy, 1966; Cooper, 1980; Graham and Hardwood, 1982). The data used to define the clear-zone distances suggested in RDG are based on limited empirical data that were extrapolated to provide information for a wide range of conditions (Graham and Hardwood, 1982; AASHTO, 2011). Current international practice for determining clear-zone widths is also largely based on the research and practices discussed in AASHTO (2011).

A considerable number of studies have identified various contributing factors to ROR crashes based on a variety of data collection and data analysis methods. Lord et al. (2011) investigated the factors contributing to ROR crashes on two-way two-lane rural roads in the state of Texas. The authors divided the contributing factors into three groups, comprising highway design characteristics (i.e., lane width, shoulder width and type, roadside design, pavement edge drop-off, horizontal curvature and grades, driveway and pavement surfaces, and traffic volume), human factors (i.e., speeding, alcohol and drug use, and age and gender), and other factors (i.e., time of day, vehicle type). The results revealed that, compared to tangent sections, wider shoulders yielded greater safety on horizontal curves. Additionally, most ROR crashes occurred on weekends, which is attributed to people driving under the influence (DUI). Unlike driveway density, which had a little impact on ROR crashes, lighting conditions had a significant influence on the probability of a ROR crash occurrence. Liu and Subramanian (2009) evaluated various contributing factors associated with single-vehicle ROR crashes. Their results showed that horizontal road alignment, area type, speed limit, roadway geometric characteristics, and lighting conditions significantly affect the frequency and severity of ROR crashes. In an attempt to identify the factors contributing to ROR crashes, McLaughlin et al. (2009) obtained the dataset of a 100-car naturalistic driving study. In each car, several software and hardware instruments had been installed to collect data. In the study, a ROR event was identified as having occurred when the subject vehicle passed or touched a roadway boundary (e.g., edge line marking and pavement edge). The study results revealed that a single factor contributed to 75% of the ROR events, followed by two other factors contributing 22%. The analysis results showed that the most common factors contributing to ROR events included: distraction, following at a short distance, low friction, narrower lane, and roadside geometric configurations. Additionally, 36% of the ROR events involved distractions due to non-driving tasks and 30% of the ROR events happened on road curves.

In another study conducted by the National Highway Traffic Safety Administration (NHTSA), driver inattention, driver fatigue, roadway surface conditions, driver blood alcohol presence, drivers' level of familiarity with the roadway, and driver gender were identified as the most significant factors contributing to ROR crashes (Liu and Ye, 2011). Jalayer and Zhou (2016a) presented a new approach for evaluating the safety risk of roadside features for rural two-lane roads based on reliability analysis. The authors confirmed that reliability indices could serve as indicators to gauge safety levels. Eustace et al. (2014) used generalized ordered logit regression to identify the most significant factors contributing to severe ROR crashes (i.e., injury and fatal). Their results demonstrated that driver conditions (e.g., impaired drivers), road alignments (e.g., curves), roadway characteristics (e.g., grade), gender (e.g., male), and roadway surface conditions (e.g., wet) increased the likelihood of severe ROR crashes. Roque and Cardoso (2014) investigated the relationship between ROR crash frequency and traffic flows with different functional forms. In an attempt to determine the contributing factors to unforgiving roadsides, Roque et al. (2015) collected ROR crash data on freeway road sections in Portugal and developed multinomial and mixed logit regression models. The empirical findings of their study indicated that critical slopes and horizontal curves significantly contributed to fatal ROR crashes. In 2015, the American Traffic Safety Services Association (ATSSA) published an executive summary booklet of various case studies to educate transportation practitioners regarding ROR crashes and associated safety countermeasures (American Traffic Safety Services Association (ATSSA, 2015). In this booklet, countermeasures are categorized as signs (e.g., chevron pattern), pavement safety (e.g., high friction surface treatments), and roadside design (e.g., clear zone improvements). The study results revealed pavement safety countermeasures, compared to other categories, to be the most effective in reducing total ROR crash frequency and severity. Gong and Fan (2017) used mixed logit models to model single-vehicle ROR crashes on rural highways. Rusli et al. (2017) employed a random parameters negative binomial model to explore single-vehicle crashes on mountainous roads.

Few studies have looked at the probability of vehicles involved in run-off-road events exceeding different encroachment distances. Zegeer et al. (1987) reported that for generally unobstructed flat ground, a provision of 5 to 20 feet for the roadside safety recovery corridor width might reduce accident rates from 13% to 44%. Lee and Mannering (2002) showed that ROR crash frequencies can be reduced by decreasing the distance from outside shoulder edge to guardrail, and increasing the distance from outside shoulder edge to light poles. Using crash data on rural roads in Victoria, Jurewicz and Pyta (2010) showed that even for very wide clear zones (> 29.5 feet) there were still a significant number of ROR crashes. Doecke and Woolley (2011) used in-depth crash investigation data of 132 Australian ROR crashes and computer simulation modelling to assess clear-zone widths and the appropriateness of barrier protection. This study showed that when a vehicle is out of control it will travel well beyond a 29.5 feet clear zone if it is not impeded by a roadside hazard. More recently, Jamieson (2012) showed similar results, using the same method and New Zealand data to investigate vehicle encroachments on horizontal curves.

Regarding the methodology used in this study, few past studies have applied a hazard-based duration model to highway safety. Duration models have been extensively used in fields such as biometrics, social sciences, and industrial engineering to determine causality in duration data. Sharman et al. (2012) compared parametric and non-parametric hazard-based duration models to evaluate the stop duration of commercial vehicles in urban areas. Lin et al. (2016) employed a combined M5P tree and hazard-based duration model for predicting urban freeway accident duration. Using a hazard-based duration model, Yang et al. (2015a) investigated the crossing behavior of cyclists and electric bike riders at signalized intersections. In another study, Yang et al. (2015b) used a joint hazard-based duration model to explore various covariates related to pedestrian crossing behavior and pedestrian waiting times at signalized intersections. Using an accelerated failure time (AFT) hazard-based model, Li et al. (2017) investigated the significant contributing factors associated with the duration of crashes. Fu et al. (2016) also used a parametric duration model to describe and model drivers' brake perception–reaction times with respect to the yellow signal at signalized intersections equipped with and without a countdown timer.

We note that although a large number of studies are related to ROR crashes, to our knowledge, no previous studies have investigated the effects of various factors such as roadway and roadside geometric design features on the distance traveled by an errant vehicle in a ROR crash, which we address in this paper. We use an efficient and practical methodology, the hazard-based duration model, to gain a better understanding of the distance traveled by errant vehicles in ROR crashes and their associated factors. Of particular interest to this study are overturn and fixed-object crashes.

Our study findings provide valuable insights into the underlying relationship between risk factors, crash injury, and the distance traveled by an errant vehicle in a ROR event. These findings will also help to promote the implementation of more efficient roadside safety countermeasures to mitigate ROR crash severity.

2. Methodology

Hazard-based duration models are typically used to study the conditional probability of a time duration ending at time t, given that the duration continued until time t (Washington et al., 2011). Several previous studies have employed hazard-based duration models to spatial settings (Waldorf, 2003; Anastasopoulos et al., 2012, 2017). By using hazard-based duration models, it is possible to model the distance traveled by an errant vehicle from the moment it hits a fixed object or overturns until the moment the vehicle stops on the roadside. With this approach, additional insights can be obtained regarding essential survival effects, such as how the probability of a vehicle immobilizing changes over the distance already traveled. For this purpose, "survivor" refers to any vehicle that continues to move in a roadside encroachment. Hazard-based duration models can account for the possibility of changes in the vehicle stop times in ROR crashes with distance traveled. Since the speeds of vehicles decrease over the distance traveled after an impact, one would expect the probability of vehicle immobilization to increase with distance. In addition, the characteristics of drivers, vehicles, and infrastructures may influence the distance traveled. According to Washington et al. (2011), probabilities that change with time are ideally suited to hazard-function analyses. To determine the distance traveled by an errant vehicle, hazard-based models consider the probability that a distance traveled Δ is greater than or equal to distance δ, with the survival function, $S(\delta)$, written as follows:

$$S(\delta) = \Pr(\Delta > \delta) = 1 - Pr(\Delta \leq \delta) = 1 - F(\delta) \tag{1}$$

where $F(\delta)$ is the cumulative distribution function of distances traveled.

The hazard function, $h(\delta)$, is defined as the conditional probability of a roadside encroachment ending at some distance δ, given that a vehicle has not stopped until distance δ, and is written as follows:

$$h(\delta) = \frac{f(\delta)}{1 - F(\delta)} = \frac{f(\delta)}{S(\delta)} \tag{2}$$

where $f(\delta)$ is the density function of distances traveled. In this case, the hazard function gives the rate at which distances traveled during roadside encroachments end at distance δ, given that they have lasted to distance δ. If the hazard function is upward sloping over the distance traveled ($dh(\delta)/d\delta > 0$), then the probability that a vehicle will stop soon increases the longer the distance already traveled. If the hazard function is downward sloping over the distance traveled ($dh(\delta)/d\delta < 0$), then the probability that a vehicle will stop soon decreases the longer the distance already traveled. And, if the hazard function is constant over the distance traveled ($dh(\delta)/d\delta = 0$), then the probability that a vehicle will stop is independent of the distance traveled.

We used the Kaplan–Meier estimator to measure the distance traveled until the car stops on the roadside. In addition, the distance traveled by errant vehicles in ROR crashes is affected by several factors. A primary objective of this study is to accommodate the effects of the explanatory variables on the distance traveled. The impact of these variables can be considered using a proportional hazards approach. In this case, the explanatory variables act multiplicatively on the baseline hazard function (Vadeby et al., 2010; Anastasopoulos et al., 2017) as follows:

$$h_i(\delta) = h_0(\delta)\exp(\beta X_i) \tag{3}$$

where $h_0(\delta)$ is the baseline hazard denoting the hazard that occurs when all elements of the explanatory variables vector are zero, X_i is a vector containing the p explanatory variables, which may depend on distance traveled δ, and β is a $p \times 1$ vector of the estimable coefficients.

Two alternative methods can be used to account for the effect of the explanatory variables, including fully parametric and semi-parametric hazard-based duration models (Van den Berg et al., 2012). Either method can be employed to study the distance traveled by errant vehicles. The fully parametric method comprises extensions of existing parametric failure time models (e.g., Weibull, exponential and log-logistic models) and uses re-parameterizations to include covariates (Yang et al., 2015a). Conversely, a semi-parametric approach is distribution-free and contains less severe assumptions regarding the underlying distribution of failure time (Balakrishnan and Rao, 2004). According to Bhat (2000), the estimates generated using a semi-parametric method are consistent, and the loss of efficiency may not be significant even when a parametric form is appropriate.

The Cox proportional-hazards model has the flexibility to accommodate a wide range of hazard function forms and is the most commonly used semi-parametric hazard-based duration model (Moore, 2016; Yang et al., 2015a). The individual hazard function $h_i(\delta)$ is semi-parametric and consists of two parts: a non-parametric part, $h_0(\delta)$, and a parametric part, $exp(\beta X_i)$. In a nonparametric proportional hazard-based duration model, the baseline hazard function $h_0(\delta)$ follows a discrete distribution, and observations are grouped into duration intervals rather than exact distances to the observed stop (Sharman et al., 2012). This model predicts the hazard (or the probability) of an observed stopping in each interval. In this approach, the baseline hazard, $h_0(\delta)$, is equal for all individuals. Therefore, individual differences are not considered when the model is making an estimate, but are considered later when changes in risk are investigated by the hazard function (Vadeby et al., 2010). The Cox model is based on an assumption of homogeneity in the survival distribution across individuals. Unobserved heterogeneity arises when factors not captured by the covariates influence the durations (Bhat, 1996; Hojati et al., 2014). If there is heterogeneity, the coefficient estimates will be inconsistent, and the interpretation of the results may be incorrect (Nam and Mannering, 2000). According to Bhat (1996), the random effects estimator is a typical procedure used to control for unobserved heterogeneity. Furthermore, one main assumption in the Cox model is that the observed distances are independent (Yang et al., 2015a). However, in practice, this assumption may be violated since some errant vehicles in this study may leave the roadway at the same location on the same day, due to effects of weather on the pavement surface. Therefore, these observations would not be independent since each vehicle in a group would share the same situational factors.

Expanding the proportional hazards model to include frailty, an unobserved random effect, allows for a model association between individual duration distances within a group. Specifically, assuming there are m groups with n_i individuals in the i^{th} group, with X_{ij} being the independent variable vector for the j^{th} individual in the i^{th} group, the hazard function of the j^{th} individual in the i^{th} group is as follows:

$$h_{ij}(\delta) = h_0(\delta)\exp(\beta X_{ij} + u_j),\ i = 1,\ \ldots, m,\ j = 1,\ \ldots, ni \tag{4}$$

where $h_0(\delta)$ is the baseline hazard and u_j is a random effect specific to individual j. Random effects are assumed to be normally distributed with a mean of zero. In duration models, heterogeneity can be handled using a log-normal distribution. A positive random effect u_j implies that individual j has a greater baseline hazard than the average individual and a negative u_j implies a lower than average hazard (Xia et al., 2015).

In the Cox proportional-hazards model, the hazard ratio (HR) is a measure of the relative importance of the explanatory variables concerning hazard, while controlling for distance. The HR is often used to interpret results predicted by the Cox proportional-hazards model (Li et al., 2009) and can be obtained by the exponentiation of each regression coefficient. Specifically, the HR indicates the time rate of stopping at any distance during the study period, compared to that of the reference category. If HR = 1, then the explanatory variable in the model does not affect and does not change the baseline hazard, $h_0(\delta)$. If HR < 1, then the time rate of stopping is decreased throughout the study period. Conversely, if HR > 1, the time rate of stopping is increased throughout the referred period (Hosmer and Lemeshow, 1999). One feature of Cox mixed-effects regression models is that the variance of the random effect is directly interpretable because it is modeled on the log-hazard scale. In fact, the exponentiation of the square root of the variance components provides information regarding HRs associated with the random effects (Giolo and Demétrio, 2011; Pankratz et al., 2005).

Cox proportional-hazards models are widely cited in the literature. For a detailed description of these models, readers are referred to Cox and Oakes (1984) and Moore (2016). In this study, we use likelihood ratio statistics to calculate the goodness-of-fit of the models. We performed all statistical analyses using *R Version 3.4.2* (R Development Core Team, 2011) and the *coxme* package (Therneau, 2015).

3. Data

In this study, we used North Carolina crash data, which we obtained from the FHWA's Highway Safety Information System (HSIS). The HSIS database contains four sub-files, including accident, vehicle, occupant, and roadway. When the sub-files are linked together, variables such as case number, vehicle number, county, route number, and milepost can be of interest. In North Carolina, a crash is reported if it involves personal injury or if the property damage exceeds $1000. For a complete description of the linking process, readers are encouraged to refer to the HSIS North Carolina Guidebook (Council et al., 2014). Given the focus of this study, we considered for further analysis only single-vehicle ROR crashes that occurred due to collisions with fixed objects and overturning. We note that the HSIS database encompasses a five-level injury severity scale, including: (1) fatality (K), (2) incapacitating injury (A-injury), (3) non-incapacitating injury (B-injury), (4) possible injury (C-injury), and (5) no injury (PDO). Based on this categorization, we identified 293 (1.5%) fatal crashes, 323 (1.7%) incapacitating-injury, 2831 (14.6%) non-incapacitating-injury, 4376 (22.6%) possible-injury, and 11505 (59.5%) no-injury crashes in the crash dataset. The final dataset consists of 19466 crashes including 2009 (10.3%) overturn crashes and 17457 (89.7%) fixed-object crashes. The dataset contains information regarding a number of attributes related to the study crashes. Those that proved to be relevant for explaining the distance traveled by errant vehicles are listed in Tables 1 and 2, depending on whether the variables are continuous or categorical, respectively.

The estimated vehicle speed upon impact was considered in the analysis but was not significant in either model. One possible reason for this might be related to errors associated with the estimates of the impact conditions made by investigating police officers. According to Mak et al. (2010), it is reasonable to expect that estimates of impact speed would be based mostly on the judgment of the investigating police officers and rarely on any step-by-step reconstruction of the crashes. Even in the case of reconstructed crashes, ROR crashes pose special problems unless the officer is also knowledgeable of the impact performance of roadside features.

4. Results and discussions

As described in Section 3, we applied the Cox proportional-hazards modelling method to all the ROR crashes data. We constructed two separate Cox mixed-effects regression models for overturns and fixed-object crashes to explore the differences between these two groups, and included the case number as a random factor. In this analysis, we selected a host of variables from five broad categories: seasonal variables (i.e., clear weather, daylight, and wet), roadway variables (i.e., AADT, speed limit, shoulder width, rural, and two-way), crash variables (i.e., collisions with roadside obstacles), vehicle-related information (i.e., point of contact, and airbag deployment), and driver characteristics (i.e., driver condition, driver injury severity, occupant ejection, and driver gender). Altogether, we calibrated 22 parameters across two models to identify the potential effects of these different factors. Table 3 shows the estimation results for overturns and fixed-object crashes.

The likelihood ratio (LR) statistics of these two models are 177.4 and 1656.9, which are higher than the $\chi 2$ statistical values, with 9 and 18 degrees of freedom, respectively, at any reasonable level of significance. We used the Z-test to examine the statistical significance of each variable and considered only statistically significant explanatory variables in the final specification models. We used a minimum confidence level of 85% as a criterion, which was met by all the independent variables in the two calibrated models. As mentioned above, we conducted this study to investigate risk factors via a retrospective duration analysis of ROR crash data and used the models for explanatory purposes (within the range of values observed, only), for which lower p-values are acceptable (Washington et al., 2011). Based on the obtained results, we found all the independent variables in the fixed-object crashes duration model to be statistically significant at the 0.05 level. Similarly, most of the independent variables in the overturns duration model were statistically significant at the same level, which demonstrates that these factors had significant effects on the distances traveled by errant vehicles during roadside encroachments. Moreover, we identified unobserved heterogeneity in both models, which indicates the presence of factors other than those included in the models that affect the distance traveled by an errant vehicle.

Fig. 1 shows estimates derived by the nonparametric method of the errant vehicles' distances traveled for overturns and fixed-object crashes. This figure also shows the estimated probability that errant cars continue to move after they hit a fixed object or overturn – the so-called survival probability. Survival probability can be divided into two parts depending on the gradient. First, a rapid fall in the first 1 foot indicates that a significant number of vehicles would stop with only a negligible distance traveled. The proportion of fixed-object crashes with a negligible distance traveled was larger than that for overturns (22% vs. 14%). Next, the survival probability decreased gradually with increasing distance traveled. In addition, the medians of the distributions were 36 feet (overturns) and 29 feet (fixed-object crashes), which indicates that more than half of the observed crashes do not exceed 36 feet. The 25% quantiles of the distributions were 78 feet and 80 feet for overturns and fixed-object crashes, respectively, indicating that approximately 25% of the observed vehicles traveled at least 78 feet.

In the Cox proportional-hazards model, the effects of independent variables on the baseline hazard function are multiplicative. A positive sign of the parameter estimate suggests an increase in the hazard function and a decrease in the distance traveled, which is associated with an increase in that independent variable. The hazard rate would change by $[\exp(\beta_i) - 1] \times 100\%$ with an independent variable change of one unit (Yang et al., 2015a). The effects of independent variables are

Table 1
Descriptive statistics of the continuous variables.

Type of crash	Variable	Description	Mean (Std. Dev.)	Minimum	Maximum
Overturns	Distance traveled (ft)		60.008 (79.062)	0	999
	Roadway Variables				
	Speed limit (mph)	Speed limit at the location of the crash (mph)	52.598 (8.149)	20	70
Fixed-object crashes	Distance traveled (ft)		63.366 (98.021)	0	1421
	Roadway Variables				
	Speed limit (mph)	Speed limit at the location of the crash (mph)	53.631 (9.048)	20	70
	AADT (vpd)	Average Annual Daily Traffic	15333.880 (27383.540)	50	183000
	Shoulder Width (ft)	Paved shoulder width (Right)	6.496 (3.562)	0	22

Table 2
Descriptive statistics of the categorical variables.

Type of crash	Variable	Description	Percentage	Frequency
Overturns	**Seasonal Variables**			
	Clear weather	1 = if the crash occurred with clear weather conditions / 0 = otherwise	70.2% / 29.8%	1411 / 598
	Daylight	1 = if the crash occurred during daylight / 0 = otherwise	63.3% / 36.7%	1271 / 738
	Wet	1 = if the road surface was wet when the crash occurred / 0 = otherwise	13.5% / 86.5%	272 / 1737
	Vehicle Information			
	Airbag deploy	1 = if the vehicle's airbag was deployed when the crash occurred / 0 = otherwise	56.9% / 43.1%	1143 / 866
	Driver Characteristics			
	Normal condition	1 = if the physical condition of the driver when the crash occurred was apparently normal / 0 = otherwise	81.6% /18.4%	1640 / 369
	Driver PDO	1 = if no injury for the driver / 0 = otherwise	39.9% / 60.1%	801 / 1208
	Male	1 = if male driver / 0 = otherwise	73.4% / 26.6%	1474 / 535
Fixed-object crashes	**Seasonal Variables**			
	Clear weather	1 = if the crash occurred with clear weather conditions / 0 = otherwise	57.6% / 42.4%	10049 / 7408
	Roadway Variables			
	Rural	1 = if the crash occurred in a rural road / 0 = otherwise	90.3% / 9.7%	15763 / 1694
	Two-way	1 = if the crash occurred in a two-way, not divided road / 0 = otherwise	71.5% / 28.5%	12483 / 4974
	Crash Variables			
	Tree	1 = if first harmful event is collision with tree / 0 = otherwise	0.8% / 99.2%	148 / 17309
	Non-breakaway pole	1 = if first harmful event is collision with luminaire pole non-breakaway / 0 = otherwise	0.2% / 99.8%	31 / 17426
	Breakaway pole	1 = if first harmful event is collision with luminaire pole breakaway / 0 = otherwise	0.1% / 99.9%	10 / 17447
	Sign non-breakaway	1 = if first harmful event is collision with sign non-breakaway / 0 = otherwise	1.2% / 98.8%	212 / 17245
	Guardrail	1 = if first harmful event is collision with guardrail face on shoulder / 0 = otherwise	0.7% / 99.3%	122 / 17335
	Bridge rail	1 = if first harmful event is collision with bridge rail face / 0 = otherwise	0.3% / 99.7%	57 / 17400
	Curb/Median	1 = if first harmful event is collision with traffic island curb or median / 0 = otherwise	0.3% / 99.7%	55 /17402
	Ditch	1 = if first harmful event is collision with ditch / 0 = otherwise	1.0% / 99.0%	167 / 17290
	Vehicle Information			
	Front of the vehicle	1 = if the point of contact of the vehicle was its central front/ 0 = otherwise	10.3% / 89.7%	1801 / 15656
	Airbag deploy	1 = if the vehicle's airbag was deployed when the crash occurred / 0 = otherwise	65.6% / 34.4%	11456 / 6001
	Driver Characteristics			
	Normal condition	1 = if the physical condition of the driver when the crash occurred was apparently normal / 0 = otherwise	77.7% /22.3%	13563 / 3894
	Driver PDO	1 = if no injury for the driver / 0 = otherwise	64.1% / 35.9%	11188 / 6269
	Ejection	1 = if occupant not ejected in the crash / 0 = otherwise	97.6% / 2.4%	17041 / 416
	Male	1 = if male driver / 0 = if female driver	61.1% / 38.9%	10673 / 6784

Table 3
Cox mixed-effects model estimation results of distance traveled by an errant vehicle.

Variable	Overturns			Fixed-object crashes		
	Coefficient estimate	p-value	Hazard ratio	Coefficient estimate	p-value	Hazard ratio
Clear weather	−0.148	0.031	0.862	−0.165	< 0.001	0.848
Daylight	0.195	< 0.001	1.215	–	–	–
Wet	0.146	0.110	1.157	–	–	–
Rural	–	–	–	−0.252	< 0.001	0.777
Two-way	–	–	–	0.179	< 0.001	1.196
Speed limit	−0.013	< 0.001	0.987	−0.017	< 0.001	0.983
AADT(/10000)	–	–	–	0.029	< 0.001	1.029
Shoulder width	–	–	–	−0.015	< 0.001	0.985
Tree	–	–	–	0.698	< 0.001	2.009
Non-breakaway pole	–	–	–	0.927	0.001	2.527
Breakaway pole	–	–	–	−1.589	0.001	0.204
Sign non-breakaway	–	–	–	0.427	< 0.001	1.532
Guardrail	–	–	–	0.437	< 0.001	1.548
Bridge rail	–	–	–	0.450	0.010	1.568
Curb/median	–	–	–	−0.530	0.003	0.588
Ditch	–	–	–	0.361	0.001	1.414
Front of the vehicle	–	–	–	0.291	< 0.001	1.338
Airbag deploy	0.104	0.058	1.110	0.146	< 0.001	1.158
Normal condition	0.226	0.001	1.254	0.387	< 0.001	1.472
Driver PDO	0.510	< 0.001	1.666	0.272	< 0.001	1.312
Ejection	–	–	–	0.201	0.002	1.222
Male	−0.087	0.150	0.917	−0.117	< 0.001	0.890
Variance of log-normal random effects	0.215	< 0.001		0.482	< 0.001	
Likelihood ratio test statistics	177.4			1656.9		
Sample size	2009			17545		

discussed below.

As shown in Table 3, we found seasonal variables to be significant in estimating the distance traveled by an errant vehicle in both hazard-based duration models. More specifically, for overturn crashes, clear weather had 0.862 times the stopping hazard of other weather conditions and for fixed-object crashes, 0.848 times those of other weather

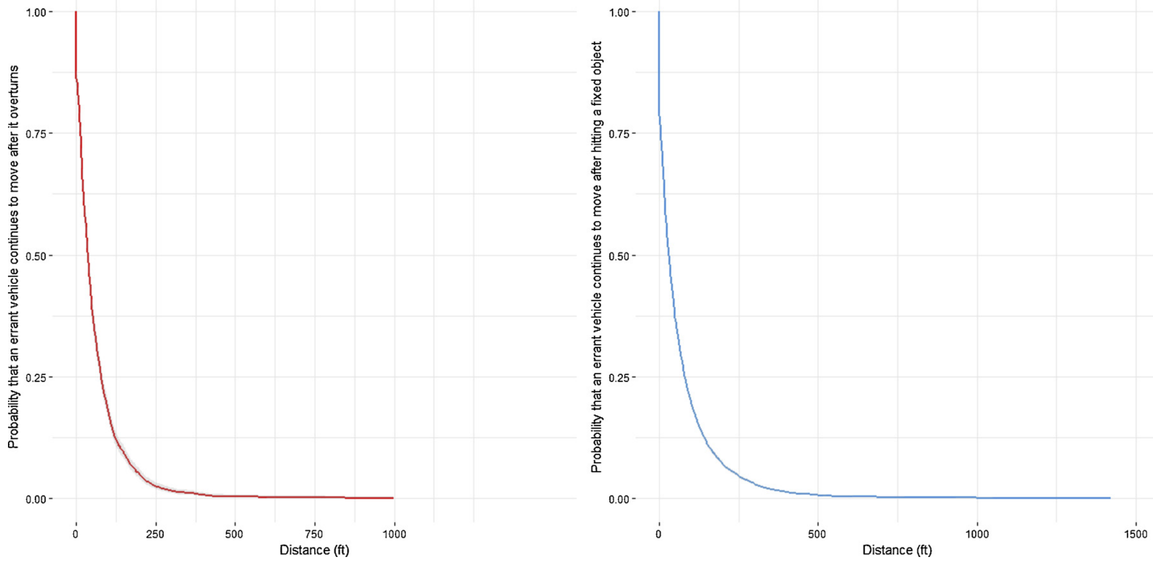

Fig. 1. Kaplan–Meier estimate of the distance traveled for (left) overturns and (right) fixed-object crashes.

conditions. This means that there are 16% and 18% decreases in the risk associated with stopping after adjusting for the other explanatory variables in the models, thereby increasing the expected distances traveled. One of the reasons for these results is the fact that motorists underestimate risk in good weather conditions, which leads to higher speeds. In this situation, higher departure speeds are expected, which makes longer distances traveled more likely. This result is in good agreement with those reported in the literature (Lord et al., 2011; Jalayer and Zhou, 2016b).

We found the lighting and road surface conditions to be significant factors in the overturns duration model. Specifically, daylight conditions had 1.215 times the stopping hazards of other lighting conditions. This indicates that there is a 22% increase in the risk associated with stopping after adjusting for the other explanatory variables in the model, resulting in a decrease in the expected distance traveled. A wet surface condition had 1.157 times the hazards of the other road surface conditions. These findings are reasonable as, during adverse weather conditions, when there is inadequate sight distance or wet surfaces, drivers tend to engage in more risk-compensating behaviors (e.g., driving at lower speeds, paying more attention to their surroundings), which results in lane departures with lower speeds. These results are consistent with the findings of Anarkooli and Hosseinlou (2016).

The estimation results presented in Table 3 identify a significant relationship between type of setting and distance traveled. Specifically, rural areas had 0.777 times the hazards of urban areas. Moreover, we found the speed limit to be a significant factor in the distance traveled by an errant vehicle in both duration models. The negative sign of the parameter estimate indicates that a decrease in the speed limit can decrease the distance traveled. Specifically, with a one unit decrease in the speed limit, the stopping hazards in overturns and fixed-object crashes will increase by 1.3% and 1.7%, respectively. We note that single-vehicle crashes in rural areas are known for their higher likelihood of fatality compared to crashes in urban areas due to the higher speed limits (Adinegoro et al., 2015).

Regarding the type of carriageway, two-way single carriageway roads had 1.196 times the hazards of one-way single and dual carriageway roads. FHWA (2018) reported that compared to one-way single or dual carriageway roads, drivers in two-way single carriageway roads tended to have lower speeds, which resulted in shorter distances traveled.

We found both AADT and shoulder width to be significant variables in the fixed-object crash duration model. By increasing one unit of AADT/10000, the hazards associated with stopping in fixed-object crashes will increase by 2.9%. One reason for this result is the fact that high traffic volume usually leads to lower travel speeds, which result in decreasing the distance traveled. This finding is consistent with those reported in the majority of studies (Underwood, 1960; Zhan et al., 2017). Moreover, decreasing one unit in shoulder width will increase the stopping hazards in fixed-object crashes by 1.5%. These results are in line with those reported by Fitzpatrick et al. (2016), which demonstrate that as the clear zone width increases, the observed speed tends to decrease.

We found the presence of several fixed objects to have significant effects on the distance traveled by an errant vehicle in fixed-object crashes. The vast majority of these objects decrease the expected distance traveled. Specifically, collisions with trees had 2.009 times the stopping hazards of other crash events and guardrails had 1.548 times the hazards of other fixed objects. These results indicate that the more rigid are the fixed objects, the less distance is traveled. These findings are in good agreement with those of other studies (Jalayer and Zhou, 2016a, b; Lord et al., 2011), which indicates that the severity of roadway departure crashes mainly depends on roadside features such as fixed objects. Interestingly, these findings demonstrate that collisions with breakaway poles had 0.204 times the stopping hazards of other crash events, which result in increases in the distances traveled by errant vehicles. This is the inherent advantage of using breakaway supports for signs and lighting, which are designed and constructed to break or yield when hit by a vehicle. Ideally, clear zones—the non-obstructed areas provided beyond the edge of traveled way—provide enough space for recovery of errant vehicles. We note that although it is not always feasible to maintain object-free roadside clear zones, crash severity can be reduced by using breakaway supports for roadside objects (Jalayer and Zhou, 2016b).

We also identified additional significant vehicle-related variables with respect to the distance traveled by an errant vehicle. A vehicle's airbag deployment had 1.110 and 1.158 times the hazards of non-deployment in overturns and fixed-object crashes, respectively. Moreover, as expected, the point of contact between the vehicle and roadside fixed objects affect the distance traveled by an errant vehicle. For instance, in fixed-object crashes, a collision with the central front of a vehicle had 1.338 times the stopping hazards of other points of contact. A possible explanation for this finding is that crashes involving the central front of vehicles are generally associated with a greater likelihood of severe single-vehicle, fixed-object crashes. These results are consistent with those of Yoganandan et al. (2010) and Nirula et al. (2003).

We also found driver characteristics to significantly affect the distance traveled by an errant vehicle. When a ROR crash occurred, a driver in apparently normal physical condition had 1.254 and 1.472 times the stopping hazards of other drivers in overturns and fixed-object crashes, respectively. This means that a driver in normal physical condition traveled less distance in ROR crashes. A study by Christoforou et al. (2013) revealed that, compared to sober drivers, intoxicated drivers cannot react appropriately in emergency situations like motor vehicle crashes.

The estimation results listed in Table 3 identify a significant relationship between the distance traveled and crash injury outcomes. Specifically, property damage only (PDO) crashes occur in shorter distances traveled in both overturns and fixed-object crash duration models. In addition, occupant ejection had 1.222 times the stopping hazards of non-ejected occupants in fixed-object crashes. Digges and Eigen (2006) found that the number of vehicle inversions that can occur in longer distances traveled significantly contributed to the injury severity of crashes. The results in both crash duration models also indicate that driver gender had a significant effect on the distance traveled by an errant vehicle. For instance, male drivers had 0.862 and 0.890 times the stopping hazards of female riders in overturns and fixed-object crashes, respectively. One reason for this result is the fact that male drivers usually take more risks than female drivers. Evans (2004) found that for each race and age, male driver crash rates far exceed female driver rates with respect to speeding due to their increased risk of crashing, being injured, or being killed.

Finally, from the estimates shown in Table 3, it can be observed that the variances of the random effects are estimated to be 0.215 ($p < 0.001$) and 0.482 ($p < 0.001$) for overturns and fixed-object crashes, respectively. Thus, this parameter is significantly different from zero, so the null of no heterogeneity can be rejected. In case of overturns, the individual-specific relative risk associated with stopping at a given point is up to 159% larger or smaller than the average risk ($\exp(\sqrt{0.215}) = 2.59$). Similarly, in the case of fixed-object crashes, $\exp(\sqrt{0.482}) = 2.00$, so the individual-specific relative risk associated with stopping at a given point is up to 2.002 times larger or smaller than the average risk.

5. Implications for design and maintenance

Once a vehicle has left the roadway, a crash may or may not occur. The end result of an encroachment depends on the physical characteristics of the roadside environment. In case of a ROR crash, the distance traveled by an errant vehicle will vary with the type of vehicle involved, its speed and impact angle, and the type of obstacle struck.

Most of the forgiving roadside design principles have been practiced in the US to varying degrees for several years and are stated on the RDG (AASHTO, 2011).

In Section 5, the Kaplan–Meier estimates showed that 25% of the distances traveled after fixed-object crashes exceed 80 feet. Our findings also showed that, although the vast majority of roadside objects decrease the expected distance traveled, the collisions with breakaway poles increase this distance. With these results, and considering an angle of departure from the roadway of 25 degrees[1], the distance traveled by an errant vehicle after hitting a breakaway support placed on the clear zone will be higher than most of the suggested clear-zone distances present in the RDG, even considering a null lateral distance from edge of traveled way to the breakaway support.

Today, more than ever, the highway designer has a significant degree of control over roadside geometry and appurtenances. Elimination of roadside hardware, their relocation to less vulnerable areas, or the use of breakaway type devices remain the options of choice in developing safer roadsides. In fact, according to the RDG (AASHTO, 2011), the use of breakaway hardware has become a cornerstone of the forgiving roadside concept since its inception in the mid-1960s.

However, recent research from the New Zealand, Australia, and the Netherlands, is raising questions about the most appropriate safety treatments for roadsides, particularly given the adoption of the Safe System approach to road safety that seeks to minimise crash severity, and the need to best allocate existing and limited resources (Jamieson et al., 2013; Jurewicz et al., 2014; van Petegem et al., 2017).

Our results suggest that encroachment data must be collected to adjust the needed clear-zone distances to present traffic conditions. The analysis presented can be helpful not only in the design of new roads but also in the future maintenance of existent roads.

6. Conclusions and recommendations

In this paper, we presented the results of hazard-based duration models with respect to the distance traveled by errant vehicles in ROR crashes, stopping hazard rates, associated risk factors, and the differences between overturns and fixed-object crashes. We collected and analyzed data for a total of 19466 ROR crashes (2009 overturns and 17457 fixed-object crashes). We used the nonparametric method to estimate vehicle distance traveled in ROR crashes from the moment the vehicle hit a fixed object or overturned until the moment it stopped on the roadside.

The first contribution of this study is that the distance traveled by errant vehicles in ROR crashes is found to be affected by seasonal variables, roadway variables, crash variables, vehicle-related variables, and driver characteristics. Our results showed that a significant number of errant vehicles will stop after travelling a negligible distance (further for fixed-object crashes than overturns), thereby indicating high risk of injury to its occupants. Then, our results also revealed that the hazard fell to a low level from 1 foot to approximately 500 feet (higher for fixed-object crashes than overturns). Over half of the observed vehicles did not exceed 36 feet and 25% of the observed vehicles traveled at least 78 feet.

The second contribution of our research is an empirical one. The results of this study provide evidence that the Cox proportional-hazards model is methodologically appropriate for investigating the distance traveled by errant vehicles in ROR crashes.

The third contribution of this study is about policy implications. Several practical countermeasures may be implemented to enhance roadside safety, including roadway cross-section improvements, hazard removal or modification, and delineation. These countermeasures have been utilized in all area types (i.e., rural, suburban, and urban) to keep vehicles in travel lanes and reduce potential collisions with roadside objects, such as trees, signs, and utility poles. However, according to our findings, the suggested clear-zone distances presented in the RDG and in international guidelines should be reviewed based on actual encroachment data.

This exploratory empirical travel distance analysis of errant vehicles after hitting a fixed object is complementary to the traditional and well-established encroachment modeling. We expect these results to provide a better understanding of errant vehicle behavior in ROR crashes and facilitate the planning and design of appropriately forgiving roadsides for errant vehicles leaving the carriageway. Our findings could also encourage policymakers to make the necessary effort to collect current encroachment data.

As in many other studies, this study has some limitations. First, some of our findings are based on a limited number of events. Peduzzi et al. (1995) published an influential article examining the effect of the number of events per variable (EPV) on the accuracy of the estimation of regression coefficients for the Cox proportional-hazards model. The number of events is defined as the number of subjects for whom an event was observed to occur. Based on the simulation results, the

[1] The small car impact angle used in Manual for Assessing Safety Hardware (MASH) (AASHTO, 2009)

authors recommended that at least 10 EPV be observed to enable an accurate estimation of the regression coefficients. In the case of breakaway poles, the EPV is 10. Therefore, we should be cautious when generalizing some of our study conclusions to different ROR scenarios. The investigation of a larger number of ROR crashes might be required in future research to enable expansion of and generalization regarding the model's applicability. Secondly, we identified the presence of unobserved heterogeneity in the duration models. This means that some other factors not included in this study may influence the distances traveled by errant vehicles in ROR crashes. Therefore, we need to collect data on more variables (particularly roadway and crash variables) to further explore these unobserved factors and thereby enhance the accuracy of our estimations.

Possible extensions of this study can focus on two aspects: crash data and model development. The development of similar analyses based on data collected for other types of crashes such as multi-vehicle crashes is desirable. Additionally, other modelling approaches should be explored for estimating the distance traveled in ROR crashes, such as accelerated failure time models and machine learning methods.

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