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Evaluating the influence of crashes on driving risk using recurrent event models and Naturalistic Driving Study data

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ABSTRACT
Dramatic events such as crashes could alter driver behavior and change driving risk during post-event period. This study investigated the influence of crashes on driving risk using the 100-Car Naturalistic Driving Study data. The analysis is based on 51 crashes from primary drivers. Driving risk is measured by the intensity of safety-critical incidents (SCI) and near-crashes (NC), which typically occur at a high frequency both before and after a crash. We applied four alternative recurrent event models to evaluate the influence of crashes based on actual driving time. The driving period was divided into several phases based on the relationship to crashes, and the event intensities of these periods were compared. Results show a reduction in SCI intensity after the first crash ($intensity rate ratio = 0.82$; 95% CI $[0.693, 0.971]$) and the second crash ($intensity rate ratio = 0.47$; 95% CI $[0.377, 0.59]$) for male drivers. No significant response to the first crash was observed for females, but SCI intensity decreased after the second crash ($intensity rate ratio = 0.43$; 95% CI $[0.342, 0.547]$). The findings of this study provide crucial information for understanding driver behavior and for developing effective safety education programs as well as safety counter measures.

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Recurrent event models; frailty models; Naturalistic Driving Study; driving risk; transportation safety

1. Introduction

Driver behavior is a critical contributing factor to traffic safety. It has been estimated that more than 90% of crashes are associated with driver errors [22]. A study by Curry *et al.* [8] concluded that 95.6 % of all teen-involved severe crashes were due to driver error.

Studies have shown that driving risk decreases with increased driving experience [4, 12,23]. Studies on driver experience are typically based on measures such as years of driving and/or mileage traveled [13,23]. For example, Waller *et al.* [23] used the time passed since licensure as the measure of experience and Kaneko and Jovanis [12] considered the years of driving experience from a national less-than-truckload firm. However, experience based on years or accumulated driving mileage includes the effects of many factors. For example, drivers may engage in less risky behaviors with the increase in age; or the increased driving

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skill enables them to deal with more complex situations; or drivers may alter their driving behaviors after crash events. In fact, af Wåhlberg [1] has shown that using time and the amount of driving as a measure of experience is commonly associated with age-related changes. Therefore, it is difficult to isolate the effects of a specific associated factor if driving experience measures are used as exposure factors.

One hypothesis is that crash experience would lead to reduced driving risk. The rationale is that drivers would learn from traumatic safety events, e.g. crashes, and change their behavior correspondingly, thus reducing driving risk. From psychological perspective, Lucas [17] showed that drivers who have experienced crashes reported greater nervousness for driving than drivers without crash experience.

There are limited studies directly linking crash experience with observed driving risk. Lin *et al.* [14] evaluated the association between motorcycle crash experience and risk-taking behavior among students in Taiwan. The risk-taking behavior was assessed using a 14-item self-administered questionnaire. The crash experience was measured by self-reported crash history prior to the study, crash frequency, time elapsed since the last crash, and crash severity. af Wåhlberg [1] compared the behavior of bus drivers with and without crash experience over a three-year period. Repeated measurements of speed-change behaviors were collected. The study showed a steady decline in speed change over time for both cohorts of drivers with and without crash experience. Rajalin and Summala [20] studied the effect of fatal accidents on surviving drivers' subsequent driving behavior based on self-reported measures. The study showed that light-vehicle drivers typically returned to their 'normal' driving behavior within a few months, while heavy-vehicle drivers tended to be more cautious. Majority of existing studies are based on self-reported driving behavior including risk-taking score, speed change, and amount of driving. There is limited research using objective measure of driving behavior using in situ collected driving data, in specific, naturalistic driving data.

Naturalistic Driving Study (NDS) is an innovative approach to collect traffic-safety and driving-behavior data in situ [9], In NDS, participant vehicles are instrumented with data acquisition systems (DASs) that include cameras and various sensors to continuously monitor the driving process. The video image and kinematic measures can provide not only exact driving behavior, vehicle kinematic data, and environmental information, but also the sequence and precise time for each sub-event. The NDS provides a unique opportunity to explore the relationship between crash experience and driving behavior, and consequently risk, accessible.

NDS data provide several alternatives for measuring driving risk. Specifically, multiple types of safety-related events can be identified through kinematic signatures and confirmed through visual inspection of video recordings. Crashes, near-crashes (NCs), and safety-critical incidents (SCIs) are the major categories that are typically used. A *crash* is defined as any contact with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated. Crashes include a participants' vehicle making contact with other vehicles, roadside barriers, and objects on or off the roadway, pedestrians, cyclists, or animals. An *NC* is defined as any circumstance requiring a rapid, evasive maneuver by the participant (or his/her vehicle) or any other vehicle, pedestrian, cyclist, or animal to avoid a crash. An *SCI* is defined as an unexpected event resulting in a close call or requiring fast action (evasive maneuver) on the part of a driver to avoid a crash [9]. These safety-related events, which represent undesired safety conditions that should be avoided, are widely used in the literature as surrogates of crash for measuring driving risk [10] and are adopted in this study as measure for driving risk and driving behavior.

The current study investigates the influence of crashes on driving risk. The objective is to evaluate whether drivers drove more cautiously after a crash as measured by the SCI and NC intensity. We are also interested in the difference in how drivers responded to crashes by gender. In general, NCs and SCIs occur at a much higher frequency than crashes and multiple events would occur before and after a crash. Therefore, the recurrent events modeling approaches are appropriate for this scenario. The recurrent event models have been commonly used in clinical trials and in the manufacturing industry [2,15,24]. Andersen and Gill [2] introduced a counting process model with Cox [7] type intensity functions. The model assumes that events occur randomly and the numbers of events in non-overlapping time intervals are statistically independent. Lin *et al.* [15] proved the robustness of the inference by relaxing the Poisson-type assumption in [2]. Nielsen *et al.* [19] proposed an intensity function depending on unobservable quantities–frailties. Wei *et al.* [24] developed a stratified model to analyze multivariate failure time data without the correlation assumption. Despite the application of recurrent events modeling in other fields, transportation studies have focused more on duration models that measure the conditional probability of a crash happening given the history from the most recent crash with limited application of recurrent event models [3,5,11, 16].

In this paper, we evaluate the influence of crashes on the intensity of SCIs and NCs by treating the number of SCIs and NCs over time as counting processes. Four recurrent event models are considered and applied to data from the 100-Car NDS. The paper is organized as follows: Section 2 introduces the 100-Car NDS. Section 3 describes four intensity-based models and model comparison. A simulation study of model performance is summarized in Section 4. The application of models to the 100-Car NDS is presented in Section 5. Section 6 provides the conclusion and discussion.

2. 100-Car NDS

The 100-Car NDS was the first instrumented vehicle study undertaken with the primary purpose of collecting large-scale naturalistic driving data. Data were collected from 241 primary and secondary driver participants in northern Virginia [9]. The participating vehicles were instrumented with an advanced DAS that could collect data continuously from ignition-on to ignition-off. The collected data include five camera views, three-dimensional acceleration, GPS, front and back radar, yaw rate, etc. The study collected approximate 2,000,000 vehicle miles and 43,000 hours of driving data. The present study used data from 107 primary drivers. Three types of safety-related events were identified through a rigorous data reduction protocol [9]. The protocol includes automatic scanning kinematic variables for potential conflicts and visual confirmation by trained data reductionist. The data included in this study consist of 51 crashes, 610 NCs, and 6,659 SCIs.

Table 1 shows the average rate for both SCIs and NCs by gender, age, and total number of crashes. Event rate is calculated as the number of events per hour of driving. In general, SCIs occur 8–10 times more frequently than NCs across all groups of drivers. Higher SCI and NC rates are associated with drivers who experienced more crashes.

Table 1. SCI/NC rate by groups.

		Age group					
		< 30 (49 subjects)		31–55 (44 subjects)		> 55 (14 subjects)	
Total number of crash		F	M	F	M	F	M
0	Number of driver	11	15	10	26	4	7
	SCI rate[a]	0.18	0.15	0.15	0.11	0.04	0.1
	NC rate	0.02	0.02	0.02	0.01	0.01	0.02
1	Number of driver	10	3	2	4	1	2
	SCI rate	0.27	0.26	0.41	0.22	0.16	0.14
	NC rate	0.03	0.02	0.04	0.03	0.06	0.01
2	Number of driver	4	6	0	2	0	0
	SCI rate	0.52	0.33	.	0.27	.	.
	NC rate	0.05	0.03	.	0.02	.	.

Note: [a]Number of event per hour per driver.

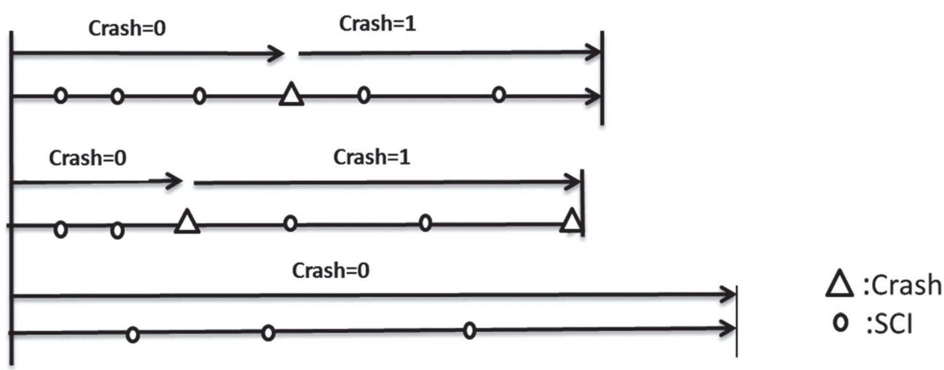

Figure 1. Data collection structure.

The data structure is shown in Figure 1, where each horizontal line represents the driving record of one driver. Drivers were subject to different numbers of crashes, NCs, and SCIs at different time points throughout study. We focused on the actual driving time. Non-driving time when the vehicle was not in use was excluded. The data processing for SCIs and NCs is similar. Driving period for each driver was divided into several phases based on its relationship with crashes: before the first crash (coded as 0), between the first and second crash (coded as 1), and after the second crash (coded as 2). Driving period was included in the model as an external and independent factor on SCI and NC intensity. To evaluate the potential confounding and interacting effects, gender and the age of the driver when first enrolled in the study were also evaluated.

3. Models

Assume a single recurrent event process is observed from time $t = 0$ to a censoring or stopping time τ. Let $0 < T_1 < T_2 < \cdots$ denote the event times, where T_k is the time to the kth event. The associated counting process $\{N(t), 0 \leq t\}$ records the cumulative number of events generated by the process. $N(t) = \sum_{k=1}^{\infty} I(T_k \leq t)$ is the number of events occurring over the time interval $(0, t]$. $Y(t) = I(t \le \tau)$ indicates whether the process is under observation at time t. The intensity function of the process gives the instantaneous probability of an event occurring at t and is defined as

$$\lambda(t \mid H(t)) = \lim_{\Delta t \to 0} \frac{\Pr[\Delta N(t) = 1 \mid H(t)]}{\Delta t}, \tag{1}$$

where $\Delta N(t) = N(t + \Delta t^-) - N(t^-)$ is the number of events in the interval $[t, t + \Delta t]$ and $H(t) = \{N(s),\ 0 \le s < t\}$ denotes the history of the process up to time t [6]. Note that $N(t)$ only contains the state of the process at time t, but $H(t)$ includes all the previous status.

This intensity function can accommodates various data structures, models, and dependence structures. Four specific models are introduced and compared as follows.

3.1. Andersen–Gill model

A commonly used and fundamental model in the recurrent event literature is the Poisson process model or Andersen–Gill (A–G) model [2]. The A–G model assumes events occur randomly in such a way that the number of events in non-overlapping time intervals are statistically independent. The overall intensity function of the Poisson process is

$$\lambda_i(t \mid \boldsymbol{z}_i(t)) = \lambda_0(t) \exp[\boldsymbol{z}_i'(t)\boldsymbol{\beta}], \tag{2}$$

where $i = 1, \ldots, m$ represents an individual. Baseline intensity $\lambda_0(t)$ is a nonnegative integrable function. $\boldsymbol{z}_i(t)$ is a vector of fixed or time-varying external covariates associated with subject i and acts multiplicatively on the baseline, and $\boldsymbol{\beta}$ is a vector of regression parameters of the same length as $\boldsymbol{z}_i(t)$. As can be seen from the definition, the A–G model assumes that the probability of an event in $(t, t + \Delta t)$ may depend on t but not on $H(t)$. Cumulative intensity, denoted as $\mu(t) = \int_0^t \lambda(t)\,\mathrm{d}t \quad t > 0$, is continuous and finite for all $t > 0$ and can be explained as the average number of events occurring in time period $(0, t]$.

The estimation of coefficients ($\hat{\boldsymbol{\beta}}$) can be derived from maximizing log partial likelihood (PL) [6], which is given as follows:

$$\log(\mathrm{PL}) = \sum_{i=1}^{m} \sum_{j=1}^{n_i} \left\{ \boldsymbol{z}_i(t)'\boldsymbol{\beta} - \sum_{k \in R_{ij}} \exp[\boldsymbol{z}_k(t)'\boldsymbol{\beta}] \right\}. \tag{3}$$

n_i is the total number of events of subject i, R_{ij} consists of all subjects who are at risk at given t_{ij}. The baseline function can be estimated by inserting $\hat{\boldsymbol{\beta}}$ into the equation for log PL and is given as follows:

$$\hat{\lambda}_0(t) = \frac{\sum_{i=1}^{m} Y_i(t) dN_i(t)}{\sum_{i=1}^{m} Y_i(t) \exp[\boldsymbol{z}_i(t)'\hat{\boldsymbol{\beta}}]}, \tag{4}$$

where $Y_i(t)$ indicates whether subject i is under study at time t, and $\sum_{i=1}^{m} Y_i(t) dN_i(t)$ is the total number of events at t.

3.2. Stratified A–G model

A common scenario for actual collected data is that subjects are sampled from subgroups of individuals with varying intensity functions. An effective way to accommodate this situation is to stratify the baseline functions into strata. This model assumes that baseline functions vary among strata while coefficients remain the same. The stratification model is shown:

$$\lambda_{ri}(t \mid \boldsymbol{z}'_{ri}(t)) = \lambda_{0r}(t) \exp[\boldsymbol{z}'_{ri}(t)\boldsymbol{\beta}], \tag{5}$$

where $r = 1, \ldots, R$ indicates stratum level, $\lambda_{0r}(t)$ is the baseline function for stratum r, and $\boldsymbol{z}_{ri}(t)$ is the corresponding covariates vector for subject i in strata r, $1 \leq i \leq m_r$.

The estimation procedure for the stratified model is similar to that of the A–G model and the log PL is as follows:

$$\log(\mathrm{PL}_{\mathrm{str}}) = \sum_{r=1}^{R} \sum_{i=1}^{m_r} \sum_{j=1}^{n_{ri}} \left\{ \boldsymbol{z}_{ri}(t)'\boldsymbol{\beta} - \sum_{k \in R_{rij}} \exp[\boldsymbol{z}_{rk}(t)'\boldsymbol{\beta}] \right\}. \tag{6}$$

3.3. Shared frailty model

In applications involving multiple subjects, individual subject heterogeneity is often presented. Heterogeneity describes variation among individual intensity rate functions, after taking condition on covariates. The heterogeneity implies within-subject variation in event occurrence is larger than is accounted for by a Poisson process. To capture the relation of the correlated observations, shared frailty models have been developed in which the event times of one subject share an unobserved random effect [18,19]. This shared individual random effect model accounts for the variation beyond that could be explained by covariates.

The shared frailty model assigns a random effect, u_i, $i = 1, \ldots, M$ to each subject acting multiplicatively on the Poisson intensity model. The intensity function is formed as

$$\lambda_i(t \mid u_i, \boldsymbol{z}_i(t)) = u_i \lambda_0(t) \exp[\boldsymbol{z}'_i(t)\boldsymbol{\beta}], \tag{7}$$

where the random terms $u_i, \ldots, u_m$ are assumed to be independently and identically distributed with mean 1 and distribution function $G(u)$. Frailty implies that events occur at a faster rate for those individuals with $u_i > 1$. A variety of distribution can be assumed for $G(u)$ including gamma, inverse Gaussian, and lognormal [25]. We adopted the lognormal distribution.

The regression coefficient $\boldsymbol{\beta}$ in Equation (7) can be estimated by either E–M algorithm or maximizing penalized partial likelihood (PPL). Therneau *et al.* [21] have proved that the solution to lognormal shared frailty models by the E–M algorithm is closely linked to PPL estimation. The logarithm of PPL is given as follows:

$$\log(\mathrm{PPL}) = \sum_{i=1}^{m} \sum_{j=1}^{n_i} \left\{ \boldsymbol{z}_i(t)'\boldsymbol{\beta} - \sum_{k \in R_{ij}} \exp[\boldsymbol{z}_k(t)'\boldsymbol{\beta}] \right\} - \frac{1}{2\sigma^2} \sum_{i=1}^{M} \boldsymbol{\gamma}'\boldsymbol{\gamma}, \tag{8}$$

where $\boldsymbol{\gamma} = (\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_m)$.

The maximization of this approximate likelihood is a double iterative process that alternates between the following two steps:

(1) For a fixed value of σ^2, find the best covariates estimation by maximizing the penalized partial log likelihood, log(PPL)
(2) For fixed values of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, calculate the REML estimation of $\hat{\sigma}^2 = (\hat{\boldsymbol{\gamma}}'\hat{\boldsymbol{\gamma}} + \text{trace}(H_{22}^{-1}))/m$ in which H_{22}^{-1} is the inverse of the second derivative matrix associated with the frailty terms.

The estimation for the baseline function is given as Equation (9), which is the same as the A–G model with an offset of estimated random effects.

$$\hat{\lambda}_0(t) = \frac{\sum_{i=1}^{m} Y_i(t)dN_i(t)}{\sum_{i=1}^{m} Y_i(t)\exp[\boldsymbol{z}_i(t)'\hat{\boldsymbol{\beta}} + \hat{\gamma}_i]} \tag{9}$$

3.4. Stratified shared frailty model

The stratified shared frailty model incorporates both stratified A–G model (5) and shared frailty model (7):

$$\lambda_{ri}(t \mid \boldsymbol{z}_{ri}(t), \gamma_{ri}) = \lambda_{0r}(t)\exp[\boldsymbol{z}_{ri}(t)'\boldsymbol{\beta} + \gamma_{ri}], \tag{10}$$

where $r = 1, \ldots, R$ indicates stratum level, i.e. number of crashes in this study. $\lambda_{0r}(t)$ represents the baseline function for stratum r. $\boldsymbol{z}_{ri}(t)$ is a vector of covariates for subject i in strata r, $1 \le i \le m_r$.

$\boldsymbol{\beta}$ is estimated by maximizing PPL, similar to the previous shared frailty model in Section 3.3. The baseline estimation for stratum r is given as follows:

$$\hat{\lambda}_{0r}(t) = \frac{\sum_{i=1}^{m_r} Y_{ri}(t)dN_{ri}(t)}{\sum_{i=1}^{m_r} Y_{0r}(t)\exp[\boldsymbol{z}_{ri}(t)'\hat{\boldsymbol{\beta}} + \hat{\gamma}_{ri}]}, \tag{11}$$

where m_r is the number of subjects in strata r and $Y_{ri}(t)$ is an indicator of whether subject i in strata r is still under study at time t.

3.5. Model fitting

Cox–Snell residuals are used for checking the overall fit of the models [6]. For the case of several processes $i = 1, \ldots, M$, with intensity $\lambda_i(t)$, Cox–Snell residuals are defined as

$$r_{ij} = \int_{t_{i,j-1}}^{t_{i,j}} \hat{\lambda}_i(s)\,\mathrm{d}s, \tag{12}$$

where $j = 1, \ldots, n_i + 1$. $t_{i,0}$ and t_{i,n_i+1} are the start and stop times for subject i. $\hat{\lambda}_i(t)$ is the estimated intensity rate. If the model fitting is good, r_{ij} should behave according to a censored sample from a unit exponential distribution. A plot of the estimated cumulative intensity rate of the residuals versus the residuals should be a straight line through the origin with a slope of one [6].

4. Simulation study

4.1. Simulation setup

We conducted a simulation study to evaluate the performance of the alternative approaches. The simulation setup is analogous to the real situation and described as follows:

(1) The driving time for 50 subjects was generated from a normal distribution with a mean of 335 and a standard deviation of 160, which was estimated from the 100-Car Study Data.
(2) For each subject, up to two crashes were generated based on the intensity function:

$$\lambda_i(t) = \tfrac{1}{150}. \tag{13}$$

The rate $\frac{1}{150}$ was selected based on the crash rate estimated from 100-Car data. The rate implies that on average one crash will occur for every 150 hours of driving. Other baseline rates were also evaluated and the model performance was robust to the change in baseline rate. Gender and other external factors were not considered in the simulation. Crash intensity was restricted to be constant over time. Crashes were considered to occur independently. If a simulated crash occurred later than the driver's study time, the crash would be censored.
(3) After generating censor time and crash time, the intensity function for each driver is defined as follows:

$$\begin{aligned}\lambda_{ri}(t) = \frac{1}{c_r} t^{k_r - 1} \times \exp\{&\beta_1(\text{sex}_{ri} = M) + \beta_2(I_{ri}(t) = 1) + \beta_3(I_{ri}(t) = 2) \\ &+ \beta_4(I_{ri}(t) = 1)(\text{sex}_{ri} = M) + \beta_5(I_{ri}(t) = 2)(\text{sex}_{ri} = M) + \gamma_{ri}\},\end{aligned} \tag{14}$$

where
(a) $r = 1,2,$ or 3, indicates stratum level. Drivers in level 1 do not experience any crashes, drivers in level 2 have only 1 crash, and drivers in level 3 have two crashes.
(b) Baseline functions depend on two parameters, c and r, which can vary from stratum to stratum, as denoted by c_r and k_r. $k_r > 1$ indicates that the SCI rate increases over time. $k_r = 1$ corresponds to a constant rate, while $k_r < 1$ means a decreasing rate.
(c) $I_{ri}(t)$ is a time-varying crash indicator. It takes a value of 1 when t is between the first and second crash and 2 when t is larger than the second crash time.
(d) β_1 is gender effect; β_2 is the first crash effect for female drivers; β_3 is the second crash effect for female drivers; $\beta_2 + \beta_4$ is the first crash effect for male drivers; $\beta_3 + \beta_5$ is the second crash effect for male drivers.
(e) $\gamma_{ri} \sim N(0, \sigma),\ r = 1, \ldots, 3;\ i = 1, \ldots, 50$ are independent frailty terms.

4.2. Simulation results

In order to cover a sufficient large range of parameter space, 24 settings with different baseline parameter combinations, as well as various combinations of gender and crash effects were tested. In each setting, 500 repeats were generated and two models were implemented:

a stratified frailty model and a frailty model. Because of space limits, we only provide results for selected scenarios.

Table 2 shows results from settings where three strata share the same scale parameter c but different shape parameters k (Setting I), share the same shape parameter but different scale parameters (Setting II), and share different scale parameters as well as shape parameters (Setting III). In Setting II, both models performed well with an average coverage probability (CP) around 95% and small bias (1–3 % difference). The stratified frailty model does not show a great benefit over the frailty model because the variation among strata is proportional and thus can be explained through frailty terms. In Settings I and III, the CP of stratified frailty model remains around 95%, while the frailty model performs poorly, with the CP as low as 20% (does not show). We also evaluated model performance at a higher level of heterogeneity (Setting IV), where frailty terms follow $N(0, 1)$. With a higher level of heterogeneity, larger bias and empirical standard error were observed for the fixed-effect estimation (β_1). Bias and empirical standard deviation of other effects remain similar. We also tested the performance of the stratified frailty model when there is no

Table 2. Simulation results.

Parameter	True value	Mean	Bias	SE[a]	SEM[b]	CP[c]
Setting I: $k = (0.9, 1, 1.2)$ $c = (0.2, 0.2, 0.2)$						
β_1	−0.2	−0.227	−0.027	0.315	0.24	85.4
β_2	0	−0.001	−0.001	0.065	0.058	95
β_3	−0.6	−0.598	0.002	0.077	0.07	93.2
$\beta_2 + \beta_4$	−0.2	−0.198	0.002	0.066	0.064	95.4
$\beta_3 + \beta_5$	−0.7	−0.691	0.009	0.08	0.075	94.6
σ	0.75	0.73	−0.02	NA	NA	NA
Average sample size		7867				
Setting II: $k = (1, 1, 1)$ $c = (0.1, 0.2, 0.3)$						
β_1	−0.2	−0.192	0.008	0.236	0.26	94.4
β_2	0	0.003	0.003	0.077	0.075	94.4
β_3	−0.6	−0.586	0.014	0.102	0.097	95.2
$\beta_2 + \beta_4$	−0.2	−0.196	0.004	0.08	0.083	95.8
$\beta_3 + \beta_5$	−0.7	−0.69	0.01	0.103	0.103	95.2
σ	0.75	0.712	−0.038	NA	NA	NA
Average sample size		4306				
Setting III: $k = (.95, 1.1, 1.22)$ $c = (0.2, 0.17, 0.15)$						
β_1	−0.2	−0.198	0.002	0.159	0.173	95.8
β_2	0	−0.001	−0.001	0.059	0.062	94.8
β_3	−0.6	−0.597	0.003	0.078	0.078	95.6
$\beta_2 + \beta_4$	−0.2	−0.198	0.002	0.069	0.068	94.2
$\beta_3 + \beta_5$	−0.7	−0.693	0.007	0.082	0.083	94
σ	0.5	0.464	−0.036	NA	NA	NA
Average sample size		6397				
Setting IV: $k = (.95, 1.1, 1.22)$ $c = (0.2, 0.17, 0.15)$						
β_1	−0.2	−0.161	0.039	0.323	0.301	91.6
β_2	0	−0.003	−0.003	0.056	0.055	96
β_3	−0.6	−0.595	0.005	0.083	0.069	94.2
$\beta_2 + \beta_4$	−0.2	−0.202	0.002	0.061	0.06	95.2
$\beta_3 + \beta_5$	−0.7	−0.691	0.009	0.087	0.073	95
σ	1	0.937	−0.063	NA	NA	NA
Average sample size		9112				

Notes: [a]Empirical standard error.
[b]Mean of standard error.
[c]Coverage probability.

stratification. Three baseline functions were set with the same c and k. Although the stratified frailty model is more complicated than the situation requires, a 95% CP on average indicates a credible and stable estimation.

In summary, a stratified frailty model is capable of accommodating possible variation among groups without losing power to test for effects of interest. If subjects behave differently with various intensity functions, aggregating them together will mask the effect of covariates at the individual level.

5. Application results

We applied four models to the 100-Car NDS data. Three covariates were incorporated into

Table 3. Results of stratified shared fraity model on SCI and NC.

	Crash Effect	Estimate	Intensity rate ratio (CI[a])	Pr > ChiSq
SCI	1 vs. 0 Female	0.109	1.115 (0.960,1.296)	0.155
	2 vs. 1 Female	−0.839	0.432 (0.342,0.547)	<.0001
	1 vs. 0 Male	−0.199	0.820 (0.693,0.971)	0.021
	2 vs. 1 Male	−0.751	0.472 (0.377,0.590)	<.0001
NC	1 vs. 0 Female	−0.117	0.890 (0.551,1.438)	0.633
	1 vs. 0 Male	−0.646	0.524 (0.314,0.874)	0.013

Note: [a]95% Confidence interval.

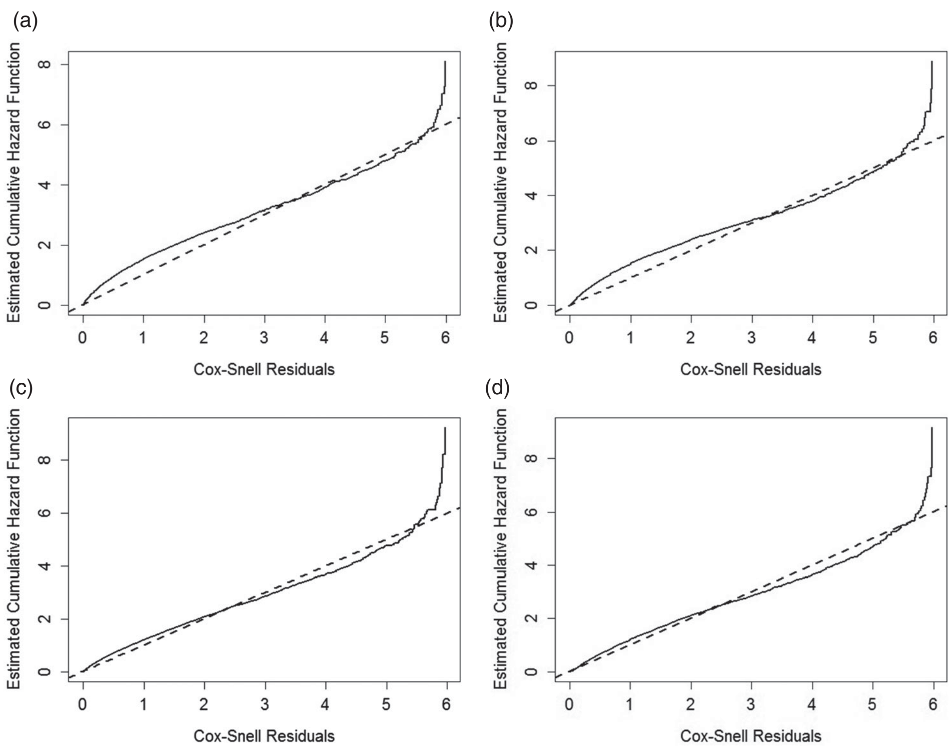

Figure 2. Cox–Snell residual plots for SCI. (a)A–G model. (b) Stratified A–G model (c) Frailty model. (d) Stratified frailty model.

the model: gender (G), age at which the driver first enrolled in the study, and crash effect based on the driver's relationship with crashes (0 for before first crash, 1 for between first and second crash, and 2 for after second crash). Crash effects were considered as a categorical variable to be tested and estimated individually. Since the study lasted for one year, age was considered to be constant.

SCIs and NCs were treated as two counting processes and were evaluated separately. As shown in Table 3, the intensity rate ratio for SCI is 0.8 (95% CI [0.693, 0.971]) between after and before the first crash for males. There is no significant effect observed for female drivers after the first crash, with an intensity rate ratio of 1.115 (95% CI [0.96, 1.296]). In contrast, SCI risk drops sharply after the second crash for both females and males, with corresponding rate ratios of 0.432 (95% CI [0.342, 0.547]) and 0.472 (95% CI [0.377, 0.59]), respectively. Compared to SCI events, NCs were observed much less frequently. Four females experienced two or more crashes in the study as shown in Table 1. One issue

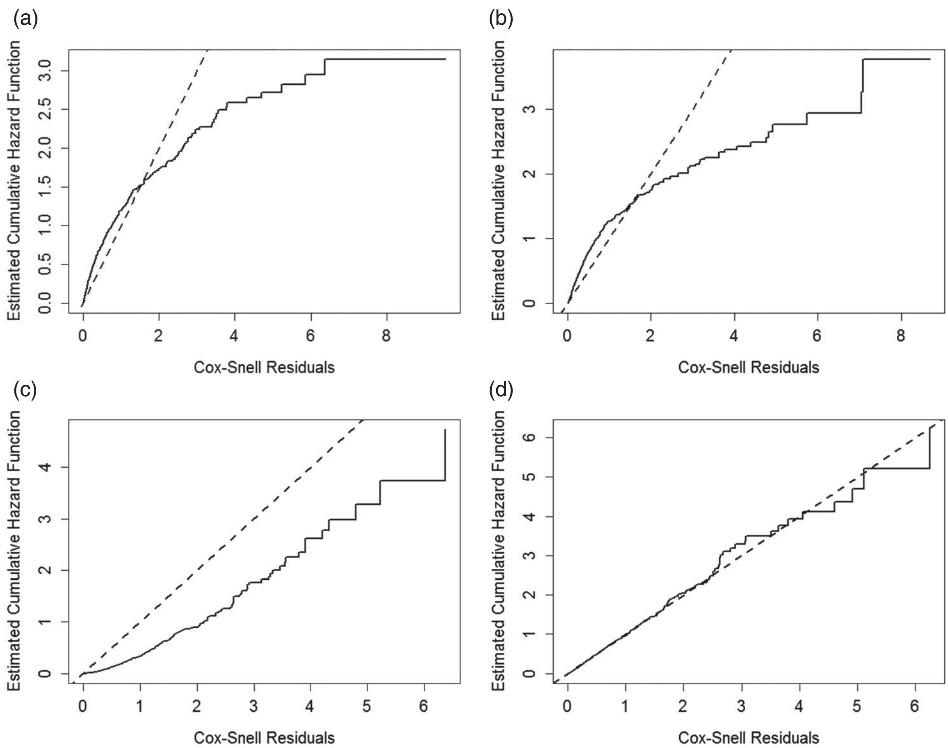

Figure 3. Cox–Snell residual plots for NC. (a)A–G model. (b) Stratified A–G model. (c) Frailty model. (d) Stratified frailty model.

Table 4. Distribution of extreme Cox–Snell residuals on SCI.

Quartile	96%	96.5%	97%	97.5%	98%	98.5%	99%	99.5%	100%
A–G	3.90	4.16	4.69	5.38	6.04	7.34	9.67	16.16	88.95
Stratified A–G	3.89	4.21	4.59	5.06	5.85	7.14	9.01	15.40	71.00
Frailty	3.77	4.02	4.32	4.64	5.12	5.68	6.76	8.73	36.73
Stratified frailty	3.71	3.97	4.21	4.52	4.88	5.43	6.37	8.11	34.72

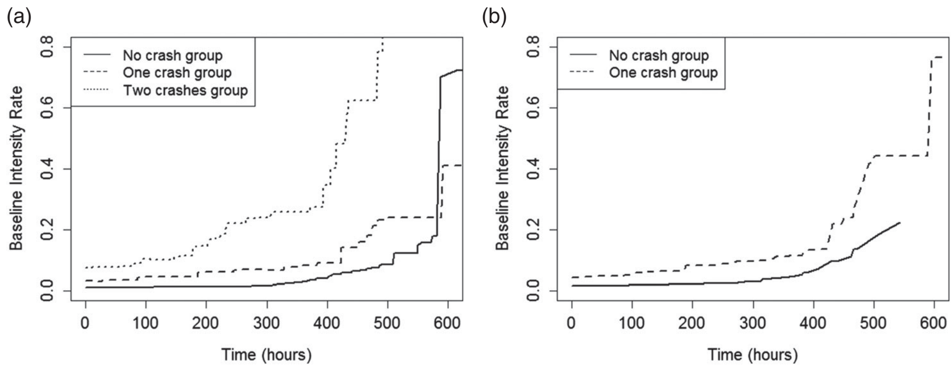

Figure 4. Baseline intensity rate estimation for SCI (left) and NC (right).

is that only one of the drivers had more than one NC recorded after the second crash. For the other three drivers, the second crash was the last driving record. Consequently, estimation of second crash effect for female drivers depends heavily on one specific driver, which may lead to an individual crash impact rather than a population-wise effect. Thus, we decided to use time up to the second crash only and evaluate the influence of the first crash on NC. Intensity rate after the first crash is 0.52 times (95% CI [0.314, 0.874]) the rate before a crash for male drivers. Females do not show a significant decreasing trend after a crash.

Figures 2 and 3 show the Cox–Snell residual plots of four intensity- based models for residuals of SCI and NC, respectively. As mentioned in Section 3, if the model is specified correctly, Cox–Snell residuals follow an exponential one distribution.

The distribution of residuals for SCIs shows a heavier tail compared to an exponential one distribution. For residuals larger than 6, the percentage varies from 1% to 2% from model to model. The probability associated with large (> 6) Cox–Snell residuals is 0.25% for an exponential one distribution. These extreme residuals lead the fitting to depart from a straight line. Long intervals between two SCI events are the major source of the extreme residuals, such as a 20-hour gap compared to a 5-hour gap on average. We have examined those long gaps. It is possible that this was caused by missing event identification during the data reduction process. For this reason, we present the distribution of extremely large residuals in Table 4 and set the upper limit of the residual to 6. It can be shown that the model fits reasonably well for the majority of data points.

For NCs, the residual plots of the stratified frailty model are much closer to a straight line compared to the other three models, indicating the best model fitting. In order to evaluate difference among strata, the estimated baseline intensity functions of SCIs and NCs were explored by the stratified frailty model in Figure 4. It can be concluded that the intensity rates for different strata are not identical, which supports the stratified models.

6. Conclusion and discussion

This study evaluated the influence of crashes on driving risk using 100-Car NDS data. The results suggest that crashes have a positive effect on driver behavior with lower SCI intensity after crashes. Drivers might either learn from the crashes experience or be more attentive while driving, which is reflected in the reduced SCI intensity within a short window after crashes. In addition, the study indicates that female and male drivers showed different response to crashes and the number of crashes also impact driver behavior. Male drivers responded to both the first crash and the second crash with a lower SCI intensity after each crash. Females showed no significant response to the first crash but did show a decreased SCI intensity after the second crash. These findings provide crucial information for understanding driver's response to dramatic safety events and can be critical for development safety education programs and safety counter measures.

We evaluated and compared four intensity-based recurrent models based on the characteristics of the data. Safety outcomes, including SCIs and NCs, are used as markers for driving risk. The simulation study demonstrated that the stratified frailty model is capable of accommodating possible variation among groups without losing power to test for effects of interest. If subjects behave differently among various levels, aggregating them together will mask the effect at the individual level. We also observed robust performance of the stratified frailty model when subjects are not from different levels. Application the models to the data suggest that the stratified frailty model fits the context of the study and provides the best model fitting for the data.

There are a couple of limitations of this study. First, the individual driver risk variation might be confounded with the observed effect. Second, the study is based on a relative small number of crashes with mild crash severity. With larger NDS data sets becoming available, such as the Second Strategic Highway Research Program (SHRP 2) NDS, more concrete evidence will be available on the influence of crashes on driver behavior and potentially the influence of crashes by severity.

Disclosure statement

No potential conflict of interest was reported by the authors.

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