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Using naturalistic driving data to explore the association between traffic safety-related events and crash risk at driver level

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ABSTRACT

There has been considerable research conducted over the last 40 years using traffic safety-related events to support road safety analyses. Dating back to traffic conflict studies from the 1960s these observational studies of driver behavior have been criticized due to: poor quality data; lack of available and useful exposure measures linked to the observations; the incomparability of self-reported safety-related events; and, the difficulty in assessing culpability for safety-related events. This study seeks to explore the relationships between driver characteristics and traffic safety-related events, and between traffic safety-related events and crash involvement while mitigating some of those limitations. The Virginia Tech Transportation Institute 100-Car Naturalistic Driving Study dataset, in which the participants' vehicles were instrumented with various cameras and sensors during the study period, was used for this study. The study data set includes 90 drivers observed for 12–13 months driving. This study focuses on single vehicle run-off-road safety-related events only, including 14 crashes and 182 safety-related events (30 near crashes, and 152 crash-relevant incidents). Among the findings are: (1) drivers under age 25 are significantly more likely to be involved in safety-related events and crashes; and (2) significantly positive correlations exist between crashes, near crashes, and crash-relevant incidents. Although there is still much to learn about the factors affecting the positive correlation between safety-related events and crashes, a Bayesian multivariate Poisson log-normal model is shown to be useful to quantify the associations between safety-related events and crash risk while controlling for driver characteristics.

1. Introduction

Road crashes are frequently characterized as rare events, often requiring many years of observation before an underlying mean can be reliably estimated. As an alternative, researchers have studied a range of safety-related events, which are similar to crashes in terms of crash risk, but without an impact (e.g. Perkins and Harris, 1967; Evans and Wasielewski, 1982; Hydén, 1987). Although driver characteristics have been shown to be associated with crash risk (e.g. Shinar, 2007; Dewar and Olson, 2001), the relationships between these characteristics and traffic safety-related events, and between safety-related events and crash involvement have been challenging to assess. Data have been of variable quality across studies because accuracy depends on the training of individual human observers. Exposure variables such as miles-traveled are typically not available for the drivers under observation, so crash rates cannot be computed. Many methods require the use of self-reported crashes and safety-related events, which raises issues concerning reliability. Finally, the culpability of the driver for the safety-related event may be difficult to determine. The methodological objective of this study is to utilize naturalistic driving study data with state-of-the-art statistical models to gain insights about driver behavior, crashes and safety related events. It is hoped that the model framework illustrates the utility of the method, so other users of naturalistic driving data may confidently adopt similar approaches.

1.1. Safety-related events analysis

There has been considerable research conducted over the last 45 years concerning the development of safety-related events for assessing traffic safety (e.g. Perkins and Harris, 1967; Datta, 1979; Hauer, 1982; Evans and Wasielewski, 1982, 1983; Risser, 1985; Hydén, 1987; Chin and Quek, 1997; Shankar et al., 2008; Tarko et al.,

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2009; Jovanis et al., 2010; McGehee et al., 2010; Guo et al., 2010; Wu and Jovanis, 2012, 2013). In the past, the goal of safety-related events research was driven by the perceived need to conduct safety analyses (e.g. identification of hazardous sites or evaluation of the effectiveness of safety countermeasure) more quickly (before a large number of crashes occur) and with more data than are typically available from law-enforcement-reported crash records (Datta, 1979; Grayson and Hakkert, 1987; Archer, 2004). Human factors have been generally considered to be among the most important factors in crash occurrence, and therefore, the relationship between driver characteristics, driving behavior, and crash involvement has also been studied using safety-related events for decades (e.g. Evans and Wasielewski, 1982, 1983; Wagenaar and Reason, 1990; Verschuur and Hurts, 2008). These types of research are often referred to as analysis of safety-related events, near crashes, risky driving, near misses, or surrogate events. The distinction between safety-related and surrogate events are that surrogate events include both crashes and near crashes with common etiologies to crashes, whereas safety-related events include only near crashes, risky driving, or near misses (Wu and Jovanis, 2012, 2013). The relationship between traffic safety-related events and crash frequency is typically studied at either segment/intersection or driver level as multiple events could occur at the same intersection/segment, and the same driver may encounter multiple events during a period of time (Jovanis et al., 2012).

The most well-known and studied safety-related event is the traffic conflict occurring at intersections. In one of the first conflict studies (Perkins and Harris, 1967), conflicts were defined based on evasive actions taken by drivers such as the appearance of brake lights or sudden lane changes. The general approach of a traffic conflict study is to collect crash and conflict data from a number of intersections, and estimate the "conversion factor," connecting the number of conflicts and traffic volume to the number of crashes (Hydén, 1987; Wu and Jovanis, 2012). Sayed and Zein (1999) conducted a similar study to validate the relationship, and they reported a statistically significant relationship between three-year crash frequency and observed conflicts at signalized intersections. Recently researchers have started utilizing field operational test or naturalistic driving study data to study run-off-road (ROR) safety-related event (e.g. Leblanc et al., 2006; Hallmark et al., 2011; Wu and Jovanis, 2012; Gordon et al., 2013).

The idea that a crash is preceded by factors more remote in time and place from the crash has been proposed for some time (e.g. Evans and Wasielewski, 1982, 1983; Evans, 1991; Dewar and Olson, 2001; Wagenaar and Reason, 1990). These factors include driver characteristics and driving behavior. Hence, safety-related driver behavior models have been proposed to connect crash involvement, driver characteristics, and driving behaviors (e.g. Verschuur and Hurts, 2008). Some of the earliest driver-based studies were conducted by Evans and Wasielewski (1982, 1983). Their studies measured following headways on the roads, and photographically recorded the license plate number to obtain the information regarding the vehicle and the vehicle owner, including age, gender, and driving record. It was shown that drivers with prior crash involvement and traffic violations were more likely to be observed at such risky headways; whereas seat-belted drivers tend to avoid risky headways. In addition, drivers under age 30, tend to take more risk in everyday driving in terms of short headways. Risser (1985) found that the sum of all errors in driving behavior shows correlation with the subjects' accidents in the past five years as well as with the subjects' traffic conflicts during a 1-h driving test.

For many years, safety-related events studies have been conducted by collecting field data at intersection/segments or by interviewing drivers. For research at intersection/segment level, researchers in the 1980s video-taped vehicle maneuvers at intersections (e.g. Hydén, 1987; Evans and Wasielewski, 1982). In recent years, researchers have started using high-definition street cameras and image recognition techniques to streamline data collection and analyses (e.g. Chin and Quek, 1997). For research at the driver level, a typical approach is to query a sample of drivers with a driver behavior questionnaire (DBQ), including self-reported driving exposure, errors, and traffic law violations, and then associate the DBQ with the frequency of their crash involvement in the past (e.g. Verschuur and Hurts, 2008).

1.2. Data analysis issues and naturalistic driving study data

Safety-related event analyses have been limited by the need to obtain exposure measures such as miles-traveled (e.g. Evans and Wasielewski, 1983). Without considering driving exposure, one would expect the safety-related events occur more frequently with tasks and activities that drivers perform more frequently (Hanowski et al., 2005). Second, self-reported safety-related events or behavior are subject to a variety of biases, making them subjective and difficult to compare across studies. Third, researchers have stressed the need to distinguish the culpability of the driver for risky driving events and crashes, i.e. to focus on those events for which the drivers are at fault (af Wåhlber, 2003). These limitations are mostly due to the constraint of data collection. In addition, traffic safety-related events are often defined using a single measure such as time to lane departure (e.g. UMTRI; Hallmark et al., 2012). Recent research has shown that there is a need to define safety-related events while accounting for event attributes (e.g. whether driver was distracted) and driving environment (e.g. daytime or nighttime condition) (Davis and Hourdos, 2012; Wu and Jovanis, 2012). Event attributes and driving environment necessitate advanced data collection techniques.

Naturalistic driving studies provide an opportunity to more precisely observe and measure safety-related events (e.g. Bareket et al., 2003; Dingus et al., 2005). Stutts et al. (2005) installed unobtrusive video units in the vehicles of 70 volunteer drivers over one-week time period to study drivers' exposure to distractions. Hanowski et al. (2005) also collected real-world driving data from truck drivers, and found that a small number of long-haul drivers were involved in a disproportionate number of distraction-related safety-related events. Guo et al. (2010) utilized the Virginia Tech Transportation Institute (VTTI) 100-Car Naturalistic Driving Study dataset to show the association between crashes and near crashes. All of these studies concluded that naturalistic driving studies could provide a useful supplement to more controlled laboratory and field studies to further our understanding of the effects of driver characteristics on traffic safety. Naturalistic driving studies cannot only precisely measure driving exposure, but also more plausibly identify the culpability of risky driving events and crashes, and disentangle different types of crashes and different causes.

There are two primary distinguishing features for a naturalistic driving study (Jovanis et al., 2011):

1. Vehicles are instrumented with video camera technologies that record the driver and the road ahead of the vehicle continuously during driving. In addition to the video, other on-board sensors continuously record vehicle accelerations in three dimensions and well as rotational motion along the same axes. Radars are often present to record proximity to other vehicles and potential obstacles on the roadway or roadside. All these data are recorded and stored within an on-board data acquisition system (i.e. DAS).
2. Drivers are asked to drive as they normally would (i.e. without specific experimental or operational protocols and not in a simulator or test track). The period of observation can vary from several weeks to a year or more.

These events are typically identified through the detection of unusual vehicle kinematics recorded electronically through accelerometers and gyroscopic sensors. Vehicle-based accelerometers are used to measure lateral and longitudinal acceleration; these measures are used individually or with time-to-collision (TTC) estimates from radar to initially identify potential events. Yaw rate level is also used to identify large heading changes within a short time period. Once identified using kinematic measures, the events are screened through use of forward and face video; they are retained if verified as safety-related events and discarded if not. Data for the period shortly before, during and shortly after the event are then preserved. The result is a set of potentially very rich data that offers insights to crashes and near-crashes that have been previously unavailable. While some aspects of events remain unobserved (e.g. the actions of drivers in other vehicles and events beyond the range of cameras and sensors), it is an unquestioned advantage to observe the actions of individual drivers, over long periods of times, including crash and near-crash involvements. Naturalistic driving has been applied to studies of drivers from the regular driving population (Dingus et al., 2005), truck drivers (Hanowski et al., 2005, 2007a,b; Fitch et al., 2008), young drivers (Simons-Morton et al., 2012), and older drivers.

1.3. Recent research on safety-related events analysis at driver-level using naturalistic driving study data

Shankar et al. (2008) proposed driver-based analysis of naturalistic driving data as part of a broader discussion of naturalistic driving study (NDS) data analysis paradigms. Some of the paradigms were empirically tested as part of a subsequent report (Jovanis et al., 2012). Guo et al. (2010) and Guo and Fang (2013) are among the few early studies that research into the relationship between crashes and near crashes at individual driver level. Guo et al. (2010) utilized naturalistic driving data to analyze the association between the frequencies of contributing factors for crashes and for near crashes. This study discussed the frequency relationship between crashes and near crashes at aggregate and individual levels. The aggregate level of analysis was conducted by studying the relationship between the total number of crashes and near crashes collected during the entire study in terms of six environmental factors. The individual level of analysis employed a Poisson regression, in which the total number of crashes for each individual driver is the dependent variable and the total number of near crashes for each individual driver is the only predictor.

Simons-Morton et al. (2012) conducted a naturalistic teenage driving study to explore whether the observed events of interest, referred to as "elevated gravitational-force" events in the study, could be used to predict at-fault crashes and near crashes for teenage drivers. The elevated gravitational-force events were events satisfying either longitudinal acceleration greater than 0.35 g, deceleration greater than 0.45 g, lateral acceleration greater than 0.05 g, or yaw rate change greater than 6° in 3 s (Table 1, Simons-Morton et al., 2012). Simons-Morton and colleagues reviewed video to determine whether a crash or near crash is the subject driver's fault. At least one crash or near crash in a month was used as the dependent variable; generalized estimating equations (GEE) logistic regression was then applied to associate the occurrence of at fault crashes or near crashes in a month with the elevated gravitational-force events rates immediately prior to the month using the logarithm of miles-driven in the same month as an offset. The GEE setting is used to control for within-subject correlation, and the use of event rate and offset accounts for miles driven. Moreover, the distinction between whether a crash or near crash is at-fault strengthens the validity of the result that crash risk was greatest in the first 6-month for teenage drivers since licensure.

This paper seeks to build on past research to provide a more generalized framework for the analysis of the relationships between driver characteristics, traffic safety-related events and crash involvement. This study proposed to apply multivariate Poisson log-normal model in an attempt to utilize the correlation between traffic safety-related events and crash involvement, which cannot only improve model precision but also mitigate potential omitting variable bias. The formulation uses hierarchical models to determine the association between the events in order to explicitly recognize the nature of the correlation between the events. The driver-based traffic safety measures in this study are single vehicle ROR safety-related events. The next section describes modeling considerations and the methodology used to model the association between driver characteristics and the number of safety-related events. Section 3 provides a detailed description of the data used in our analysis and the screening process for the safety-related events. A discussion of results follows with conclusions and suggestions for future research.

2. Methodology

The suggestions of using near crashes to substitute crashes or combining near crashes and crashes to form a composite safety measure are viable only when the near crashes have common etiology to crashes (e.g. af Wåhlber, 2003; Wu and Jovanis, 2013). This study only focuses on single-vehicle ROR events, since these events are etiologically similar and do not involve any other road users, i.e. more at-fault than other types of events (af Wåhlber, 2003). Moreover, instead of combining different types of events or different levels of incident severity into one dependent variable, this study includes multiple dependent variables for each level of incident severity to avoid aggregation bias. Also, it may be fruitful to treat each level of incident severity as a separate model through a correlation measure, so that the relationships between different levels of incident severity can be tested. This approach obviates the need for aggregation of events and the challenges to common etiology that arises as a result.

Therefore, a model is formulated that quantifies the relationship between crashes, near crashes, and crash-relevant conflicts; these may be thought of as outcomes with an ordered level of severity, with crashes the most severe and conflicts the least. Unlike the existing literature, this formulation allows for explicit recognition of the endogenous nature of these events at the driver level by using a Bayesian hierarchical formulation.

This study seeks to explore the association between the number of traffic safety events and crashes while controlling for driver characteristics, and hence, count regression models are suitable (Jovanis and Chang, 1986; Shankar et al., 1995). Count models that are commonly used include Poisson and negative binomial regression. Recent studies have found that there is a lack of independence in different types or severity of crashes that constitute the total number of crashes (Chib and Winkelmann, 2001; Ma and Kockelman, 2006; Park and Lord, 2007; Ma et al., 2008; Yannis et al., 2008; Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009; Ye et al., 2009), which would lead to excess variation around fitted values that cannot be captured (Berk and MacDonald, 2007). Therefore, a multivariate Poisson log-normal model (MVPLN) has been proposed as a promising alternative for simultaneously modeling crash frequency in terms of different crash severity or types. Although this specification is promising and has been applied to road safety analysis, it has not been applied to a driver-level analysis.

As Ma et al. (2008) indicates, Maximum Likelihood estimation cannot be implemented for multivariate Poisson log-normal models since the resulting integral does not have a closed form. On the other hand, Bayesian methods have been gaining popularity as the approach of choice when modeling multiple levels and incorporating random effects or complicated dependence structures, such as correlated errors (i.e. multivariate normal error terms such as the ones used in this work) (Banerjee et al., 2004). Around 1990, the "Markov Chain Monte Carlo revolution" took place, and methods like the Gibbs sampler and the Metropolis algorithm were coupled with faster computing to enable evaluation of complicated integrals that are usually found in Bayesian methods (Banerjee et al.). Markov chain Monte Carlo, also known as Markov chain simulation is a general method based on drawing values of the parameters of interest from approximate distributions and then correcting those draws to better approximate the target posterior distribution (Gelman et al., 2003). Details about Markov chain simulation are beyond the scope of this paper, interested readers can refer to (Gelman et al., 2003; Congdon, 2003; Congdon, 2006).

For the models, the response variable is the number of events per driver, by severity level. In this study, the event severity levels are crashes, near crashes, and crash-relevant incidents. The formulation follows the specification in Aguero-Valverde and Jovanis (2009). The number of safety-related events is Poisson distributed:

$$y_{ik} \sim \text{Poisson}(\mu_{ik}) \tag{1}$$

where y_{ik} are the observed number of traffic events of severity k for driver i, and μ_{ik} is the expected number of traffic events for person i with event severity k. The Poisson rate is modeled as a function of the covariates following a log-normal distribution as shown is Eq. (2):

$$\log(\mu_{ik}) = \beta_{0k} + \log(\text{VMT}_i) + \sum_{j=1}^{J} \beta_{jk} X_{ik} + v_{ik} \tag{2}$$

where β_{0k} is the intercept for severity k, VMT_i is the vehicle-miles traveled by driver i, β_{jk} is the coefficient for j covariate and severity k, X_{ij} is the value of the j covariate for person i, and v_{ik} are the random effects for each event severity type. These random effects capture the extra-Poisson heterogeneity among drivers. Here, the number of vehicle-miles traveled by each driver is used as a measure of the exposure; hence, incorporated into the model as an offset.At the second stage, the coefficients (β_{jk}), including the intercepts, are modeled using flat normal priors (i.e. variance several orders of magnitude greater than the expected value of the posterior):

$$\beta_{jk} \sim \text{Normal}(0, 1000) \tag{3}$$

Now, one can assume that the random effects for each severity type are independent; therefore having the following prior distributions:

$$v_{ik} \sim \text{Normal}(0, \tau_k^{-1}), \quad k = 1, 2, 3 \tag{4}$$

where τ_k is the inverse of the variance also known as the precision. The precision has a gamma prior:

$$\tau_k \sim \text{Gamma}(0.01, 0.001), \quad k = 1, 2, 3 \tag{5}$$

with a mean of 10 and a variance of 10,000.

This specification is equivalent to the Full Bayes hierarchical univariate (multiple independent equations) Poisson log-normal specification for each severity level but it offers the advantage of being directly comparable with the multivariate specification (multiple correlated equations). For the multivariate model, correlated priors in the random effects vector are estimated using multivariate normal priors (Park and Lord, 2007; Ma et al., 2008):

$$v_i \sim N_3(\mu_i \sum) \tag{6}$$

where μ_i is a vector of zeroes $\mu_i = (0, 0, 0)$ and Σ is the variance-covariance matrix with a hyper-prior defined by:

$$\Sigma^{-1} \sim \text{Wishart}(\boldsymbol{R}, n) \tag{7}$$

where $\boldsymbol{\Sigma}^{-1}$ is a symmetric positive definite matrix, also known as the precision matrix. The Wishart distribution is a generalization to multiple dimensions of the chi-square distribution where n is the number of degrees of freedom (i.e. $n = 3$, since there are 3 levels of severity in this study) and $\mathbf{R}$ is a non-informative scale matrix:

$$\mathbf{R} = \begin{pmatrix} 0.1 & 0.005 & 0.005 \\ 0.005 & 0.1 & 0.005 \\ 0.005 & 0.005 & 0.1 \end{pmatrix} \tag{8}$$

The values of $\mathbf{R}$ were recommended by Gelman et al. (2003) and Carlin and Louis (1996) to produce a non-informative prior for the precision matrix, analogous to the non-informative gamma distribution for the prior of the univariate precision shown in Eq. (5). Furthermore, the correlation among different severities is estimated through the variance–covariance matrix:

$$\rho_{ml} = \frac{\sigma_{ml}}{\sqrt{\sigma_m^2 \sigma_l^2}} \quad \text{for} \quad m = 1, 2, ; \quad l = 1, 2, 3; \quad \text{and} \quad m \neq l \tag{9}$$

where ρ_{ml} is the correlation between m and l severities, σ_{ml} is the covariance between m and l severities, and σ_m^2, σ_l^2 are the variances for severities m and l respectively.

The same predictor would have different effects on events with different severity, but at the same time, these effects could be correlated for the same driver. It is desirable to utilize this correlation among these effects to enhance model precision. Therefore, a multivariate prior was also tested for the coefficients in the model as shown in Eq. (10):

$$\beta_j \sim N_3(\mu_j, \sum\nolimits_j) \tag{10}$$

where μ_j is a vector of zeroes $\mu_j = (0, 0, 0)$ and Σ_j is the variance–covariance matrix with a hyper-prior defined in the same way of the multivariate random effects in Eqs. (7) and (8).

3. Data description

The Virginia Tech Transportation Institute (VTTI) 100-Car Naturalistic Driving Study dataset was used for this study (Dingus et al., 2005); it initially includes 107 primary drivers, and 12–13 months of data collection for each vehicle. Prior to the study, participants were asked about demographic information, and tested for a variety of medical and psychological attributes, such as hearing, sleeping schedule, aggressive driving tendency, and life stress. A data acquisition system (DAS) was installed in each vehicle consisting of cameras for video recording, kinematic sensors, radar, lane tracking devices, and a hard drive for data storage. At certain points during the study, information from the DAS hard drive was received, and triggering software was run based on event criteria (see Dingus et al., 2005). Once certain triggers were found in the data, attributes of each event were saved from 30 s prior, to 10 s after the onset of the precipitating event. Based upon the event criteria, VTTI researchers identified 69 crashes and 9056 safety-related events (761 near crashes and 8295 crash-relevant incidents (less severe near crashes)) during the entire study. These events of interest, as a whole, span the full range of crashes and safety-related events. One should notice the screening criteria used here are different from those used in Simons-Morton et al. (2012), as discussed in Section 1.2. The sample size was reduced to 90 primary drivers (the remaining 17 drivers had incomplete information), including a total of 14 single vehicle ROR crashes and 182 single vehicle ROR safety-related events (30 near crashes and 152 crash-relevant incidents). Table 1 is a summary for the variables tested in this sample.

Table 1
Summary statistics.

Variable	Mean	Std. Dev.	Min	Max
Number of crashes during the study	0.16	0.45	0	2
Number of near crashes during the study	0.33	0.85	0	6
Number of crash-relevant incidents during the study	1.69	4.23	0	23
Number of crashes involved in the past year	1.28	1.42	0	7
Number of traffic law violations in the past year	1.49	2.02	0	16
Proportion of drivers with regular sleeping schedule	0.83	0.37	0.00	1.00
Sleeping hours per day	7.01	1.01	3.50	9.50
Cup of coffee intake per day	2.18	1.97	0.00	10.00
Drivers' age	36.26	14.41	18	68
Proportion of male drivers	0.63	0.48	0	1
Number of years with license	19.31	14.08	1.5	52
Miles traveled during the study	11892.93	5101.02	2340	23980
Proportion of driver with at least 4-year college degree	0.60	0.49	0	1
Driving stress index	260.98	18.73	220	341
Life stress index	165.91	131.47	0.00	560.00
Negative Emotions Index, reflecting negative emotions during driving	11.55	1.22	8.84	14.00
Aggressive Driving Index, reflecting intent to harm	6.14	1.14	3.45	9.06
Reckless Driving Index, reflecting reckless driving	10.31	1.14	7.24	14.00

The safety-related events vary from high to low severity. Crashes are high severity events where there is an impact between the vehicles and another object. Near crashes and crash-relevant incidents are low severity events that involve safety risk but where a crash does not occur. Specifically, a crash is defined as, "any measurable dissipation or transfer of energy due to the contact of the subject vehicle with another vehicle or object" (Dingus et al., 2005, p. xxxvi). A near crash is an event in which a crash was avoided only through an action that approached the operating limits of the driver or vehicle by means of a rapid maneuver. "As a guide: subject vehicle braking greater than 0.5 g, or steering input that results in a lateral acceleration greater than 0.4 g to avoid a crash, constitutes a rapid maneuver" (Dingus et al., 2005, p. 6). A crash-relevant incident was an event in which a crash was avoided by an extreme steering or braking input (or both) but which did not approach driver or vehicle limits. This classification is conducted after use of initial event screening criteria, as shown in Table 1.

Parameter estimates would be biased when important variables are omitted (e.g. Greene, 2003; Cameron and Trivedi, 2005). Although it is impossible to include all relevant variables in practice, it is advisable to include as many proxy variables as possible (e.g. Greene, 2003; Cameron and Trivedi, 2005). For example, young drivers are known to tend to encounter more crashes and near crashes than other drivers. Similarly, exposure measures, such as vehicle miles traveled, but it is known that vehicle-miles-traveled is correlated with not only safety performance measures but many predictors at the same time. Driver attributes and personality descriptors were obtained before and after data collection. Driver attributes include permanent characteristics such as age and years of driving experience (constant over the course of the year or so of a naturalistic study) and driving style which is intended to convey the level of risk the driver is willing to accept while undertaking the driving task. Years of driving experience were self-reported by all participants based on the number of years having a driver's license. As discussed in Jovanis et al. (2011), a driver's experience with crash outcomes may, after some period of time, affect their driving style. It is not expected that this will occur during the typical duration of a naturalistic study (one year or less) but for longer term studies it is possible that such a hypothesized change may be observable in the data set. This study recognizes that driver adaptation may occur, but is not modeled in this study.

The Dula Dangerous Driving Index (DDDI) (Dula and Ballard, 2003) was used to measure drivers' self-reported likelihood of dangerous driving. Each DDDI scale – DDDI Total, Aggressive Driving (AD), Negative Emotional (NE) Driving, and Risky Driving (RD) scales – had tests of internal reliability, and evidence of construct validity of the scales as part of initial scale development and testing (Dula and Ballard, 2003). Participants responded to the items on the following Likert scale: A = *never*, B = *rarely*, C = *sometimes*, D = *often*, E = *always*. In order to quantify DDDI, we assigned numerical values to each response (one through five for A through E, respectively). The higher the score per driver, the more dangerous the driving behavior was considered to be. The scores were rescaled by deflating the scores by the individual driver's mean score (this was an attempt to handle scaling bias). Examples of AD include positive responses to comments such as, "I verbally insult drivers who annoy me" and "I deliberately use my car/truck to block drivers who tailgate me". Examples of RD include positive responses to comments such as, "I will illegally pass a car/truck that is going *too* slowly" and "I will weave in and out of slower traffic". Examples of NE include affirmative responses to comments such as, "When I get stuck in a traffic jam, I get *very* irritated" and "I get irritated when a car/truck in front of me slows down for no reason". The Life Stress Index (LSI) questionnaire was used to obtain information about various types of stress and changes that subject drivers may have experienced in the year before the study.

The DDDI and LSI were used to describe aspects of individuals' personalities or current life experiences that may predispose them to crash, near crash or crash-relevant conflict involvement. These measures were included in the models in order to provide additional insight concerning event causality. Other researchers (e.g. Shinar, 2007), have supported the general validity of seeking to associate these types of descriptors with crash occurrence. The reliability of personality measures over time has been addressed in at least one study that found reasonable correlation (Ozkan et al., 2006). Particularly given the recent interest in aggressive driving, it seemed reasonable to explore associations between the DDDI and event odds; given that LSI measures a different dimension of stress that could affect driving, it seemed reasonable to include this measure in the models as well.

4. Results

The models were estimated using the open source software OpenBUGS (Thomas et al., 2006). For the models, 1000 iterations were discarded as burn-in, and the 100,000 iterations that followed were used to obtain summary statistics of the posterior distribution of parameters. Convergence was assessed by visual inspection of the Markov chain for the parameters. Moreover, the Monte Carlo errors for each parameter in the model are less than 5 percent of the value of the standard deviation of that parameter. The goodness-of-fit measures commonly used in Bayesian statistics are presented

Table 2
Models without correlations among the coefficients of age under 25.

	Model 1: Indep. random effects						Model 2: Corr. random Effects					
	Mean	S.D.	MC error	Sig.	2.5% CI[d]	97.5% CI	Mean	S.D.	MC error	Sig.	2.5% CI	97.5% CI
C[a]_Constant	−11.740	2.943	0.089	***	−18.520	−7.226	−10.240	2.091	0.034	***	−14.700	−6.396
N[b]_Constant	−2.335	3.014	0.033		−8.444	3.615	−3.556	2.715	0.036		−9.129	1.620
I[c]_Constant	−4.596	1.386	0.019	***	−7.369	−1.895	−4.033	1.268	0.023	***	−6.534	−1.539
C_Age under 25	1.956	0.884	0.018	***	0.400	3.882	2.008	0.770	0.013	***	0.610	3.644
N_Age under 25	0.801	0.581	0.007	*	−0.296	1.994	0.924	0.543	0.008	*	−0.135	1.994
I_Age under 25	1.063	0.531	0.008	***	0.034	2.124	1.215	0.539	0.012	***	0.173	2.301
C_Number of crashes in the past year	−0.037	0.272	0.005		−0.562	0.503	−0.137	0.223	0.003		−0.599	0.270
C_Aggressive Driving Index	0.860	0.330	0.007	***	0.297	1.571	0.718	0.278	0.004	***	0.183	1.285
C_Regular sleeping schedule (Yes/No)	−0.061	0.823	0.014		−1.616	1.647	−0.494	0.671	0.012		−1.773	0.866
N_Sleeping hours	−0.630	0.254	0.004	***	−1.194	−0.169	−0.330	0.166	0.003	***	−0.660	−0.004
N_Negative Emotions Index	0.166	0.239	0.002		−0.300	0.643	0.095	0.208	0.002		−0.313	0.504
I_Aggressive Driving Index	0.139	0.222	0.003		−0.304	0.571	0.037	0.205	0.004		−0.375	0.430
Severity corr. b/w crash and near crash							0.887	0.211	0.009	***	0.353	0.992
Severity corr. b/w crash and conflict				NA			0.896	0.210	0.009	***	0.394	0.993
Severity corr. b/w near crash and conflict							0.968	0.037	0.001	***	0.868	0.996
DIC				427.800						404.300		

** Significant at 10 percent level.
[a] Crash equation.
[b] Near crash equation.
[c] Crash-relevant conflict equation.
[d] Credible Interval.
* Significant at 20 percent level.
*** Significant at 5 percent level.

in the tables: the posterior mean of the deviance and the deviance information criterion (DIC) (Spiegelhalter et al., 2002). The posterior mean of the deviance is equivalent to the deviance estimate in frequentist statistics while the DIC is the Bayesian equivalent of the Akaike information criterion (AIC) (Spiegelhalter et al., 2002). As in the case of their frequentist counterparts, the deviance and the DIC quantify the relative goodness-of-fit of the models; therefore, they are useful for comparing models.

Four different model specifications are presented in this section. Model 1 and 2 test the correlation between crashes, near crashes, and crash-relevant conflicts while controlling for driver difference. Model 1 is referred to as independent random-effects model (univariate model), which is equivalent to model the equations in Eq. (2) separately using three Poisson log-normal models (the three equations are assumed to be independent), as shown in the left of Table 2. Model 2 is referred to as a correlated random-effects model (multivariate model), which imposes a correlation structure among the random effects to model the associations between the three equations, as shown in the right of Table 2.

A correlation structure among the coefficients of age under 25 were further appended to the model 1 and 2, respectively, leading to model 3 and model 4, to observe whether there exists any associations between the coefficients of age under 25 in the three equations. Model 3 includes a correlation structure among the coefficients of age under 25 but the random effects in the three equations are independent, as shown in the left of Table 3. Model 4 includes not only a correlation structure among the coefficients of age under 25 but also the random effects in the three equations are independent, as shown in the right of Table 3.

As discussed in Section 2, multivariate Poisson log-normal models generally provide better model fit with greater efficiency than univariate formulations. The models with a correlation structure among the random effects fit significantly better than the independent random-effects model (20 points is considered as significant, as suggested by Spiegelhalter et al. (2002)). The models with correlation structure also have smaller standard deviations of the estimated parameters (compare model 2 to model 1, and model 4 to model 3). Although the models with a correlation structure among the coefficients of age under 25 were expected to fit better than the models without it, their DICs are not statistically different (compare model 3 to model 1, and model 4 to model 2) (within five points is considered no difference, Spiegelhalter et al. (2002)). The estimated coefficients of the variables representing age under 25 were reduced by half due to the introduction of the correlation structure among the coefficients. The coefficients of age under 25 seem to be positively correlated, indicating that the greater its effect in one equation, the greater it would be in the other equations. But this association does not achieve statistical significance, i.e. the credible sets cover zero.

Since model 2 is more parsimonious than the most comprehensive model, model 4, and has the lowest DIC among all the specifications, the rest of the statistical inference is primarily based on model 2. After controlling for various potential confounders, the random effects across the three equations appear to be positively correlated, suggesting positive associations between the occurrence of crash, near crash, and critical conflicts; a finding consistent with Guo et al. (2010). These results are not surprising: the same unobservable factors, such as driving skills, behaviors, or aggressiveness, that lead to higher crash risk, also lead to more near crashes and critical conflicts. The correlations among the three levels follow an ordering: near crashes are most strongly correlated with conflicts (0.968); crashes and conflicts and crashes and near crashes have similar correlations (well within ± a standard deviation). These correlations support the general notion of crashes as rare events. While associated with both near crashes and critical conflicts, something happens during crash events that lead to a crash outcome. The correlations indicate that these factors are important; more so than factors that differentiate near crashes from

Table 3
Models with correlations among the coefficients of age under 25.

	Model 3: Indep. random effects + corr. age under 25						Model 4: Corr. random effects + corr. age under 25					
	Mean	S.D.	MC Error	Sig.	2.5% CI[d]	97.5% CI	Mean	S.D.	MC Error	Sig.	2.5% CI	97.5% CI
C[a]_Constant	−10.640	2.208	0.092	***	−15.500	−6.826	−9.947	2.019	0.070	***	−13.990	−6.165
N[b]_Constant	−1.526	2.984	0.161		−7.301	4.222	−3.179	2.736	0.140		−8.412	2.007
I[c]_Constant	−4.702	1.379	0.077	***	−7.416	−1.952	−4.058	1.296	0.068	***	−6.804	−1.532
C_Age under 25	0.938	0.686	0.015	*	−0.139	2.435	0.873	0.690	0.019	*	−0.574	2.419
N_Age under 25	0.494	0.472	0.010		−0.324	1.524	0.419	0.472	0.014		0.255	1.469
I_Age under 25	0.683	0.485	0.013	*	−0.129	1.725	0.578	0.498	0.018		−1.819	1.666
C_Number of crashes in the past year	0.021	0.236	0.003		−0.454	0.478	−0.113	0.222	0.003		−0.639	0.299
C_Aggressive Driving Index	0.837	0.278	0.011	***	0.332	1.422	0.778	0.272	0.009	***	−0.328	1.314
C_Regular sleep schedule (Yes/No)	−0.339	0.734	0.011		−1.756	1.129	−0.577	0.651	0.010		−0.320	0.740
N_Sleep hours	−0.624	0.240	0.010	***	−1.144	−0.173	−0.318	0.164	0.006	**	−0.133	0.001
N_Negative Emotions Index	0.107	0.240	0.013		−0.393	0.577	0.071	0.204	0.010		−0.354	0.465
I_Aggressive Driving Index	0.184	0.219	0.012		−0.257	0.610	0.081	0.202	0.011		−0.206	0.482
Severity corr. b/w crash and near crash							0.897	0.163	0.007	***	0.421	0.992
Severity corr. b/w crash and conflict				NA			0.908	0.150	0.006	***	0.501	0.994
Severity corr. b/w near crash and conflict							0.967	0.038	0.001	***	0.865	0.996
Age effects corr. b/w crash and near crash	0.481	0.594	0.008		−0.922	0.997	0.431	0.611	0.012		−0.922	0.996
Age effects corr. b/w crash and conflict	0.593	0.530	0.009		−0.853	0.998	0.531	0.563	0.013		−0.876	0.997
Age effects corr. b/w near crash and conflict	0.455	0.593	0.009		−0.918	0.996	0.406	0.605	0.012		−0.914	0.995
DIC				432.130						406.640		

[a] Crash equation.
[b] Near crash equation.
[c] Crash-relevant conflict equation.
[d] Credible interval.
* Significant at 20 percent level.
** Significant at 10 percent level.
*** Significant at 5 percent level.

critical conflicts. Reflecting on these findings, one is reminded again of the caution that should be applied when combining crashes with either of the other two event types.

This study initially considered including variables of drivers' gender and driving experience. Although gender has found to be associated with both the number of crashes and with crash rate normalized by distance driven (e.g. Lee et al., 1980), its effect in this study becomes insignificant after including miles-traveled. This shift to insignificance is likely due to co-linearity between gender and miles-traveled in this sample, which inflates the standard error for the coefficient of gender, and hence results in insignificance. Similarly, even though gender and driving experience were significant in the beginning, they became insignificant after including the variable of age under 25. Additional testing was conducted with a variable for drivers with driving experience less than or equal to 10 years. The results of these models (not shown) were a marginally significant increase in the expected number of near crashes, though the driving experience variable had a sign which was positive in all three event equations. Drivers under age 25 were found to have significantly greater number of crashes, near crashes, and crash-relevant incidents than other drivers in the study, an indication that these young drivers are less skilled and experienced or more likely to be distracted (Shinar, 2007). Notably, drivers under age 25 are 6.49 times more likely to be involved in a ROR crash ($6.49 = \exp(2.01) - 1$). The trend is consistent with the national statistics and past research. National statistics show that young drivers have a disproportionate number of crashes (Evans and Wasielewski, 1982, 1983) and driver under 24 years old are 2–4 times as likely to be killed in an accident as other drivers (Shinar, 2007). Moreover, as Shinar (2007) found that young drivers are especially over-represented in single-vehicle crashes, the type of event considered in this study. Use of naturalistic driving data focused on younger drivers has the potential to better understand *why* these changes in crashes are being observed. Similar testing and modeling with larger NDS data sets such as available in SHRP 2 safety may be able to yield additional insights as to crash contributing factors.

Drivers involved in more crashes in the past year were found to be less likely to be involved in a crash in the next year. Some research has found that drivers with more crash involvement in the past tend to have greater number of crashes in later years (e.g. Evans and Wasielewski, 1982), but no such effect was found in this study. The finding here is possibly reflecting regression-to-the-mean due to only one-year study period. The number of traffic law violations in the past year was also not found to affect the number of single vehicle ROR events, though Evans and Wasielewski (1982) reported that drivers with no crash or traffic violation history are less likely to be observed at risky headways (Evans and Wasielewski).

Aggressive driving remains a topic of attention in the in the popular press and research literature. Our model results show the existence of positive and substantial association between driver aggressiveness and the number of crashes. Drivers' with higher aggressive driving index were found to be more likely to be involved in a crash. A one percent increase in the scaled DULA aggressive driving index results in a 4.4 percent increase in the expected number of crashes ($4.4 = 0.718 * 6.14$).

Drivers' sleep habits and hours were found to be associated with the expected number of crashes and near crashes, respectively. Drivers with regular sleeping schedule were found to have 39 percent less expected number of crashes but not significant. Interestingly, regular sleeping habit was found to affect crash equation only. Similarly, more sleeping hours was found to be beneficial to the near crash reduction. A one percent increase in the sleeping hour results in a 2.3 percent decrease in the expected number of near crashes ($-2.3 = -0.32 * 7.01$). It should be noted that there are few studies in the past that are comparable to the findings here as most studies have primarily focused on the effects of short-term sleep restriction on driving ability and crash risk (e.g. Philip et al., 1996, 1999). Nevertheless, these findings are generally consistent with those in the past research that sleep deprivation and fatigue would reduce driving performance measures such as perception reaction time, alertness, or decision making (e.g. Shinar, 2007; Harrison and Horne, 1999; Banks and Dinges, 2007).

5. Summary and discussion

This paper studies single vehicle ROR safety-related events collected from a previous naturalistic driving study (Dingus et al., 2005) to explore the relationship between the involvement in these events and crash risk. The advantage of using naturalistic driving data to conduct a driver-level analysis includes (1) observe all traffic safety-related events with a high degree of accuracy and reliability (Dingus et al., 2005; Jovanis et al., 2011), (2) determine the culpability of the driver for the events, and (3) obtain more precise exposure measures. A Bayesian multivariate Poisson lognormal model was used to simultaneously estimate a drivers' frequency of crashes, near crashes, and crash-relevant incidents. Since this study focuses on ROR events only, the results and discussions are referred to ROR events only. Among the findings were the following:

- The correlations among crashes, near crashes, and crash-relevant incidents were significant and positive. The occurrence of near crashes and conflicts are positively and significantly correlated (Correlation coefficient = 0.97); correlations between crashes and either near crashes or conflicts were also high (Correlation coefficient = 0.87) even after controlling for all other predictors.
- Drivers under age 25 are significantly more likely to be involved in all single vehicle ROR safety-related events, an indication that these young drivers are less skilled or experienced, and,
- Drivers' sleeping habits were found to be associated with the number of crashes and near crashes. More sleeping hours was found to be beneficial to reduce near crashes.

The finding concerning the correlations between events implies that more research is needed to study what are the factors and what is the underlying mechanism that constitute the associations among crashes, near crashes, and crash-relevant incidents. The positive correlations between safety-related events and crashes suggest that there are unmeasured factors that affect crashes and safety-related events in the same direction even after controlling for exposure and other covariates. One focus for future research should be the expansion of covariates available through NDS associated with driver attributes. In addition, roadway-related covariates can be more completely added as predictors. Countermeasures related to the unmeasured covariates might be effective in reducing safety-related events and crashes in addition to countermeasures associated with the covariates in the current model.

The multivariate Poisson log-normal model (MVPLN) employed in this study is promising to be applied to other related analysis. The MVPLN model can be applied to look into different types of safety-related events other than different levels of event severities. It is likely that some driver characteristics are influential to certain types of events, but have no effect on others. A recent paper proposed a Multinomial Generalized Poisson (MGP) model to utilize correlations between different levels of crash severity into account to more precisely estimate the number of crashes at each severity level (Chiou and Fu, 2013). To the authors' best knowledge, there has not been any studies conducting comparison between the two models, and hence it is undetermined concerning with which model can provide better model goodness-of-fit. Although both MVPLN and MGP models appear to be promising in providing better modeling precision, future research of the application of these models should consider: (1) when the proportions of a certain level of crash severity, notably, fatal crash, is low, it is very likely that the standard errors of many predictors would be high, and hence only few predictors would be significant. There is a need to develop a method to overcome this limitation; (2) both MVPLN and MGP models are still not able to include crash-level information into consideration, i.e. event attributes such as daytime versus nighttime conditions; these attributes are available in NDS and likely contribute to severity level; (3) one of the most important bi-product of these two models is the correlation structure; more research is needed to discuss factors influencing this correlation.

Lastly, since a naturalistic driving study is essentially a longitudinal study to track drivers crash risk, the combination of a naturalistic driving study and the multivariate Poisson log-normal model can be extended to identify the group of drivers who tend to have more safety-related events than the average drivers. Integration of roadway inventory data with NDS would facilitate such longitudinal comparisons and inclusion of roadway and event features. Such integration is being conducted as part of the SHRP 2 safety NDS in the U.S. (TRB, 2014).

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