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Modeling the safety impacts of driving hours and rest breaks on truck drivers considering time-dependent covariates

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ABSTRACT

Introduction: Driving hours and rest breaks are closely related to driver fatigue, which is a major contributor to truck crashes. This study investigates the effects of driving hours and rest breaks on commercial truck driver safety. *Method:* A discrete-time logistic regression model is used to evaluate the crash odds ratios of driving hours and rest breaks. Driving time is divided into 11 one hour intervals. These intervals and rest breaks are modeled as dummy variables. In addition, a Cox proportional hazards regression model with time-dependent covariates is used to assess the transient effects of rest breaks, which consists of a fixed effect and a variable effect. *Results:* Data collected from two national truckload carriers in 2009 and 2010 are used. The discrete-time logistic regression result indicates that only the crash odds ratio of the 11th driving hour is statistically significant. Taking one, two, and three rest breaks can reduce drivers' crash odds by 68%, 83%, and 85%, respectively, compared to drivers who did not take any rest breaks. The Cox regression result shows clear transient effects for rest breaks. It also suggests that drivers may need some time to adjust themselves to normal driving tasks after a rest break. Overall, the third rest break's safety benefit is very limited based on the results of both models. *Practical applications:* The findings of this research can help policy makers better understand the impact of driving time and rest breaks and develop more effective rules to improve commercial truck safety.

1. Introduction

Trucks constitute a large and growing segment of highway traffic in the United States. On many rural interstate highways, trucks account for more than one-third of the total traffic (Harwood et al., 2003). Based on a report released by the Federal Motor Carrier Safety Administration (FMCSA, 2013a), the numbers of fatal crashes involving large trucks were 2983, 3271, and 3341 in 2009, 2010, and 2011, respectively. Large trucks here are defined as trucks with gross vehicle weight rating greater than 10,000 lbs (FMCSA, 2011). They accounted for around 10% of all fatal crashes during these three years. The estimated costs of these commercial motor vehicle (CMV) crashes were \$79, \$84, and \$87 billion in 2009, 2010, and 2011, respectively. These facts indicate that large trucks play a major role in fatal crashes that cost billions of dollars of loss every year. A major contributing factor to truck-related crashes is driver fatigue due to truck drivers' heavily irregular working schedules (Arnold et al., 1997; Campbell, 2002; Frith, 1994; Häkkänen & Summala, 2001; Hall & Mukherjee, 2008; Hanowski et al., 2005; Jovanis et al., 1991; Kaneko & Jovanis, 1992; Lin et al., 1993, 1994; Mackie & Miller, 1978; Saccomanno et al., 1995). This study focuses specifically on analyzing crashes involving truckload (TL) carriers, since they typically own and operate large commercial trucks. Truckload carriers (FMCSA, 2011) are companies that often contract an entire semi-trailer or intermodal container (a standardized reusable steel box that can be transferred from one transport mode to another without the need to unload and reload its contents) to a customer. They pick up a fully loaded semi-trailer or intermodal container from the shipper and send it to the receiver directly. These semi-trailers and intermodal containers generally carry a substantial amount of cargo and need to be transported over long distances. To ensure safety, their drivers' working schedules are normally set according to Hours of Service (HOS) regulations and travel distance.

Truck drivers usually have long driving hours with irregular schedules. Based on a survey conducted in Australia, Arnold et al. (1997) found that 38% of drivers drove more than 14 h per a 24-h time period. Another study by Mackie and Miller (1978) included three extensive field experiments to establish the relation between fatigue and regular and irregular schedules. They also conducted a national survey of over 500 drivers whose driving logs were

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collected from owner operators, private carrier drivers, and charter bus drivers. They implicated that driving performance (e.g., the ability to control, navigate, and guide) decreased significantly after about 8 h of driving with regular schedules, and just after about 4 to 5 h of driving with irregular schedules. Kaneko and Jovanis (1992) used cluster analysis and logit model with time-independent variables such as age, experience, driving hours, and off-duty time prior to the last trip to investigate large truck crashes. They concluded that truck crash risks were lowest in the first 4 h, gradually increased after the 4th h, and reached a peak value after 9 h of driving. Another similar conclusion was made by Frith (1994) that crash risks increased beyond 8 h after a driver's 10-h off duty. Saccomanno et al. (1995) analyzed police crash reports and commercial vehicle driver demographics, working hours, and routes. He detected a significant discontinuity in the trend of crash rate that occurred around 9.5 h of driving to a driver's shift. Before the 9.5 h, the crash rate was relatively insensitive to driving hours (0.109 crashes per million vehicle-km), and became significantly higher after 9.5 h (0.235 crashes per million vehicle-km). Campbell (2002) found that the relative risk of fatigue-involved crashes for truck drivers was 2.6 during the first 10 h, and roughly doubled to 4.7 and 4.9 between the 11th and 12th hour. In general, long driving time may directly or indirectly cause three main factors in driver fatigue: circadian rhythm effects, sleep deprivation and cumulative fatigue effects, and industrial or “time-on-task” fatigue (FMCSA, 2013b). These fatigues can eventually cause truck drivers' performance to deteriorate and contribute to crashes.

The purpose of the Hours of Service (HOS) regulations is to relieve truck driver fatigue and to reduce crashes. Rest breaks have been considered an important positive factor for improving truck driver safety. Lin et al. (1994) found that rest breaks, particularly those taken before the 6th or 7th h of driving, appeared to lower crash risk significantly. Another study (Harris & Mackie, 1972) found that rest breaks in general were valuable for driver recovery from fatigue. They further concluded that the third such break did not result in any improvements of safety performance when rest breaks were taken every 3 h. Chen and Xie (2014) reached a similar conclusion that three or more rest breaks did not bring additional significant safety benefits to truck drivers. In the new HOS rules (FMCSA, 2011), a term related to rest breaks was firstly included as “After June 30, 2013, driving is not permitted if more than 8 hours have passed since the end of the driver's last off-duty or sleeper-berth period of at least 30 minutes.”

In light of the potential significant impacts of irregular working schedules and long driving hours of truck drivers, the objective of this study is to quantify how driving hours and rest breaks influence truck drivers' crash risks. Data from two major national truckload carriers are collected and analyzed using two statistical methods. The data, methods used, and the analysis results are detailed in the remainder of this paper.

2. Statistical methods

Two statistical methods are used in this paper to analyze the impacts of driving hours and rest breaks. A discrete-time logistic regression model is used for analyzing the crash odds of driving hours and rest breaks. In the discrete-time logistics regression model, rest breaks are treated as time-independent variables. This restriction may not be reasonable, since intuitively the effects of rest breaks may change as time passes by. To address this limitation of the discrete-time logistics regression, a Cox Proportional Hazards (PH) regression model with time-dependent covariates is introduced to evaluate the transient effects of rest breaks. The Cox PH model with time-dependent covariates is based on the assumption that the safety impacts of each rest break consist of a time-independent fixed component and a time-dependent component.

To better describe the above two statistical methods, the following variables are first introduced. For driver i, t_i is used to represent the driving time duration from the beginning of a trip to the current location. Driver i may take several rest breaks during the trip, the amount of time spent on rest breaks is not counted toward the driving time t_i. For instance, driver i started the trip at 8 a.m. and finished the trip at 4 p.m. She had two rest breaks that took a total of 1 h. The total driving time for this driver is considered as 7 h, not 8 h. In this study, each driver's driving time for the entire trip is divided into 1-h intervals or periods indexed by j. t_j represents the driving time duration from the beginning of the trip to the end of time period j. Failure time t_{if} denotes the driving time duration from the beginning of the trip to the point when driver i got involved in a crash. For time period j, a driver is considered censored if her/his failure time t_{if} is greater than t_j. If t_{if} is less than t_j and greater than t_{j-1}, this driver is considered uncensored in time period j. If a driver finishes a trip without any crashes, this driver is considered censored for the entire trip. Additionally, a discrete random variable C_i is introduced. It is equal to j if driver i is involved in a crash during time period j.

2.1. Discrete-time logistic regression model

In the discrete-time logistic regression model, the survival of a driver in each time period is treated as a Bernoulli trial with two possible outcomes, representing whether driver i is involved in a crash (i.e., uncensored) or not (i.e., censored) at the end of the time period. If driver i with p different predictor values $x_{1ij}, x_{2ij}, \ldots, x_{pij}$ did not have any crashes by the end of time period $j-1$, the conditional probability for this driver to be involved in a crash in time period j is:

$$h_{ij} = \Pr\left(C_i = j | C_i \geq j,\ X_{1ij} = x_{1ij},\ \ X_{2ij} = x_{2ij},\ \cdots X_{Pij} = x_{pij}\right). \tag{1}$$

The conditional probability, h_{ij}, is a fundamental parameter of discrete-time survival analyses. Cox (1972) proposed an extension to the proportional hazards model for discrete-time survival analyses by incorporating the conditional probability (h_{ij}) of crash in time period j, given that the driver has survived the previous ($j-1$) time periods. This new model is often referred to as the discrete-time logistic regression model and is shown in Eq. (2).

$$h_{ij} = \frac{1}{1+\exp\left[-\left(\sum_{n=1}^{j}\alpha_n D_{nij} + \sum_{m=1}^{p}\beta_m X_{mij}\right)\right]} \tag{2}$$

where D_{nij} ($n = 1, \ldots, j$) is a sequence of dummy variables, indexing time periods; α_n ($n = 1, \ldots, j$) is the baseline level of hazard in each time period; and β_m ($m = 1, \ldots, p$) is the coefficient of each predictor. A logit (log odds) model of the hazard or conditional probability of crash during time period j can be obtained by rearranging Eq. (2) and taking logarithm on both sides of it. The result is shown in Eq. (3).

$$\log\left(\frac{h_{ij}}{1-h_{ij}}\right) = \sum_{n=1}^{j}\alpha_n D_{nij} + \sum_{m=1}^{p}\beta_m X_{mij}. \tag{3}$$

Parameters α_n and β_m in Eq. (3) can be obtained by maximizing a likelihood function, which is the product of two distinct components: the first component is the probability for uncensored drivers and the second one is the probability for censored drivers (Singer & Willett, 1993). The probability for driver i to be uncensored in time period j_i (i.e., driver i did not get involved in any crashes up until