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Original Research Paper

The effect of time of day on driver's injury severity at highway-rail grade crossings in the United States

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ABSTRACT

Based on the Federal Railway Administration (FRA) database, there were totally 25,945 highway-rail crossing crashes happened in the United States between 2002 and 2011. With an extensive research, analysis results showed that there were substantial differences by time of day for driver's injury severity at highway-rail grade crossings. However, there is no published study on time of day analysis of driver's injury given that a highway-rail grade crossing crash happens. This study applied ordered probit models to explore the determinants of injury severity for motor vehicle drivers at highway-rail grade crossings. The results show that motor vehicle driver's injury severity in highway-rail grade crossing crashes that happen during a.m. peak, p.m. peak, and p.m. off-peak is extremely higher than other time periods. However, speed control will significantly reduce driver's injury severity. In addition, crashes that happen during early morning, a.m. peak, and p.m. peak are more likely to be influenced by vehicle speed and train speed compared with other time periods. Paved highways will significantly help to reduce driver's injury severity at highway-rail grade crossings. Drivers during peak hours, early morning and p.m. off-peak are more likely to be influenced by unpaved roadway compared with other time periods.

1. Introduction

Vehicle-train crash collisions are the most dangerous traffic crashes at highway-rail grade crossings because the average weight ratio of a train to a motor vehicle is about 1–4000 (Yan et al., 2010). Based on the Federal Railway Administration (FRA) database, there were 25,945 highway-rail crossing crashes in the United States between 2002 and 2011. Although the annual average collision rate for highway-rail grade crossings is relatively lower compared with highway crossings, these highway-rail crossing collisions result in higher fatality rates making the study of them critically important.

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There are approximately 25,945 highway-rail grade crossings in the United States. Among these crossings, approximately 39 percent are privately owned and the other 61 percent are publicly owned. Although the number of collisions at highway-rail grade crossings has bean reduced, it is still high and needs to be further reduced.

The initial dataset obtained from the FRA database included 25,945 highway-rail grade crossing crashes that occurred in the United States from 2002 to 2011. In addition, these crashes have been distributed differently by time of day, as shown in Fig. 1. Based on previous studies, time of day is classified into the following times: (1) early morning (midnight–6:30 a.m.); (2) a.m. peak (6:30 a.m.–9:00 a.m.); (3) a.m. off-peak (9:00–noon); (4) p.m. off-peak (noon-4:00 p.m.); (5) p.m. peak (4:00 p.m.–6:30 p.m.); (6) evening (6:30 p.m.–midnight) (Stead and Bhat, 2000; Okola, 2003).

1.1. Research objectives

Limited previous studies on crash modeling at highway-rail grade crossings aimed to explore the factors that are likely to increase the crash frequency. However, in recent years, modeling driver's injury severity at highway-rail grade crossings has received numerous scholars' interests. With an extensive research, analysis results showed that there were substantial differences by time of day for driver's injury severity in highway crashes (Bougard et al., 2008; Reimer et al., 2007; Qin et al., 2006). However, there is no published time of day analysis on driver's injury severity given that a crash happened by time of day characteristics. In the following sections, a literature review and a description of the data will be provided, followed by a discussion of the model estimation results.

1.2. Literature review

Previous studies have been performed to examine the time of day as an influence factor on highway crashes instead of developing separate models by time of day.

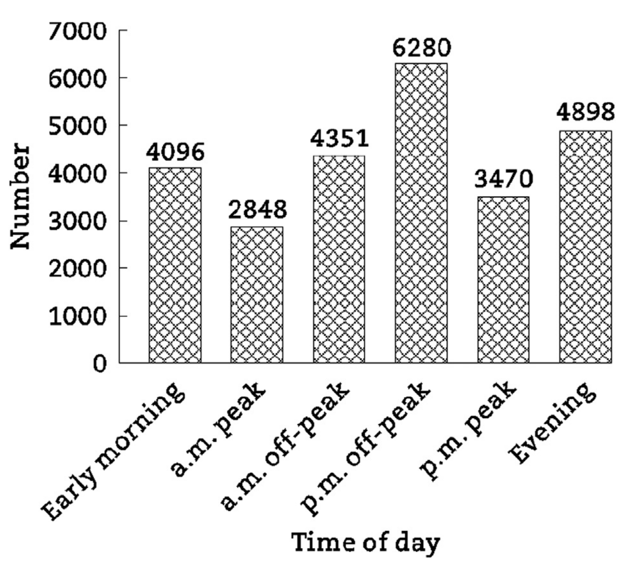

Fig. 1 – Highway-rail grade crossing crash distribution by time of day.

Motorcycle-driving performance by time of day and sleep deprivation was studied by Bougard et al. (2008). Twelve male participants voluntarily took part in four test sessions, starting at 6 a.m., 10 a.m., and 6 p.m., following a night either with or without sleep. The results indicated that motorcycle control at low speed was impacted by time of day, with an improvement in performance throughout the day.

Driving performance by time of day was examined by Reimer et al. (2007). Data were pooled from two driving simulation studies, yielding 79 participants. All subjects were English-speaking active drivers with a minimum of one year driving experience. In the first study, participants were between the age of 18 and 52. In the second study, participants were required to be either younger than 25 or older than 55. The results showed that drivers in the late afternoon consistently drove significantly slower than drivers in other time periods. Time of day had an effect on reaction time and on speed variability measures.

Young driver crashes in the UK were studied with consideration of the influence of age, experience, and time of day (Clarke et al., 2006). A sample of over 3000 crash cases was collected from midland British police forces, involving drivers aged 17–25, and covering a two-year time period (1994–1996). This method relied on the human interpretation of road crash case reported by a special team of researchers with driving experience in several types of vehicle. "Time of day" analysis suggested that the problems of crashes in darkness were not a matter of visibility, but a consequence of the way young drivers used the roads at night. As a result, the crash rate for all drivers that travelled per unit of distance was much higher during darkness than during the daylight.

A study investigated the relationship between crash occurrence and hourly volume for highway segments in Michigan and Connecticut (Qin et al., 2006). The data in this study were collected from different agency resources in the states of Michigan and Connecticut. Hourly traffic volumes from automatic traffic recorders (ATR) were gotten requested from each state's department of transportation, with crash records and road segment characteristics gathered for contiguous highway segments to ensure hourly volume consistency. The study period for Michigan ran from 1995 to 1997 and a total of 32 road segments were used. Compared with the Michigan sample, Connecticut had a smaller sample size of 17 segments along with a longer time period between 1995 and 2000. The author selected time periods of 7 a.m.–3 p.m., 3 p.m.–11 p.m, and 11 p.m.–7 a.m., in order to be consistent with commonly defined work shifts and typical definitions of morning and afternoon peak periods. The binary regression model was used to conduct Bayesian estimation of hourly exposure functions by crash type and time of day. The results revealed how the relationship between crashes and hourly volume varied with time of day, which improved the accuracy of crash occurrence predictions.

The effect of age and time of day on sleepiness for professional drivers was investigated by Otmani et al. (2005). Thirty-six young and middle-aged professional male drivers, free from any sleep disorder, took part in two simulated driving sessions; one was carried out in the afternoon (between 2 p.m. and 4 p.m.) and the other was carried out in the evening (between 11 p.m. and 1 a.m.). All the data were analyzed by ANOVA, a statistical program. Data obtained on visual analog scales (alertness and sleeping level) that were recorded before and after the driving task were analyzed with consideration of driver's age, traffic condition, time of day, and reaction time. Young professional drivers were found to be more susceptible to sleepiness and were more often involved in sleep-related crashes. Besides, they were more likely to present a strong decrease in their alertness level than middle-aged drivers while driving. The effect of time of day was clearly observed as many differences appeared between afternoon and evening session.

Driving performance was different by time of day (Lenne et al., 1997). Numerous factors contributed to the 24 h pattern of automobile crashes. In this study, 11 male subjects operated a driving simulator for 30 min at six times of day. Driving performance was measured in terms of the mean and standard deviation of lateral position and speed. This study indicated that driving performance and reaction time were affected by time of day. Driving performance was more likely to be impaired at 200 h and 600 h, and improved between 1000 h and 2200 h without an early afternoon dip. The significance of the early afternoon period and associated dips in driving performance was also highlighted.

Based on the above mentioned studies since 1990s, there is clear evidence documenting a difference in crash occurrence during different times of day. Although a few researches have investigated whether driver's performance is affected by time of day for highway crashes, no research is found to study whether driver's injury severity is influenced by time of day at highway-rail grade crossing crashes. In addition to the impact of time of day, this research will investigate the impact of highway characteristics, vehicle attributes, environmental factors, and land use factors on driver's injury severity at highway-rail grade crossings. The results can provide some additional insights into this problem and suggest some ways to improve highway-rail grade crossing safety for drivers in different travel time periods.

2. Materials and methods

As demonstrated in previous studies, driver's injury level is quite different in different time periods. Previous studies are limited in studying the entire day period. This study attempts to develop ordered probit models for different times of day and explore the effect of time of day on drivers' injury severity at highway-rail grade crossings. In addition, its objective is to identify differences in driver's injury severity in different time periods. To do this, separate models are estimated for drivers in each time period. In the following sections, the data collection, ordered probit model and statistical tests will be described.

2.1. *Data collection*

In this study, the original dataset, which was obtained from the FRA database, included 25,945 highway-rail grade crossing crashes that occurred in the United States from 2002 to 2011. Table 1 shows the frequency and percentage distribution of the variables in each of six time periods. FRA database includes both current and historical records of 80 $\times$ 10^3 to 100 $\times$ 10^3 crossings and is updated per year. In addition, it is classified into three sub-databases including the highway-rail grade crossing inventory, the highway-rail crossing history file and the highway-rail crossing crash data. These sub-databases, which are described below, are linked to each other by a common crossing ID number.

The highway-rail grade crossing inventory collects current crossing inventory which reflects the current state of each crossing with reference attributes. This database was used in this study to identify independent factors that reflect crossing-related attributes and train/vehicle traffic patterns. In the database of highway rail crossing history file, four types of information were obtained for each crash at highway-rail grade crossings: the warning device type, area type, annual average daily traffic (AADT), and percentage of trucks. Six types of factors in our final sample database are sourced from highway-rail crossing crash data including: time factors (month, hour, and a.m. & p.m.), vehicle information (vehicle speed and vehicle type), train information (train speed), weather information (visibility and weather condition), and driver's information (age, gender, and injury level). The selection of independent variables was based on previous studies (Kockelman and Kweon, 2002; Morgan and Mannering, 2011; Pai and Saleh, 2007; Zhang et al., 2011). The overall process of creating the sample database used for model estimations involved the following two steps: (1) highway-rail grade crossing data were extracted from the FRA database; (2) key variables obtained from the database were reclassified.

2.2. *Ordered probit model*

The methodology undertaken in this study includes developing, estimating, and analyzing statistical models that predict the probability of injury severity outcomes. A variety of methodological techniques have been applied to analyze crash injury severity data. Besides, three discrete driver-injury severity outcomes are considered: property damaged only (PDO), injury, and fatality. To analyze these types of discrete outcome data, researchers have used a variety of methodological approaches including multinomial logit models, ordered probit models, latent class models, nested logit models, and mixed (random parameters) logit models. A complete review of crash injury severity models and methodological approaches can be found by Savolainen et al. (2011). Statistical models such as ordered probit models are widely used to fit the ordinal structure of crash severity (Kockelman and Kweon, 2002; Lee and Abdel-Aty, 2005; Siddiqui et al., 2006; Zhang et al., 2011). The following subsections describe the ordered probit approach, and its general specification is given by Zhang et al. (2011).

$$y_i^* = X_i\beta + \varepsilon_i \tag{1}$$

where X_i is a vector of observed non-random explanatory variables measuring the attributes of crash victim i, β is a vector of unknown parameters, and ε_i is a random error term

Table 1 – Variables description.

Description		Early morning		a.m. peak		a.m. off-peak		p.m. off-peak		p.m. peak		Evening	
		Frequency	Percentage (%)	Frequency	Percentage (%)	Frequency	Percentage (%)	Frequency	Percentage (%)	Frequency	Percentage (%)	Frequency	Percentage (%)
Driver	0 = PDO	2866	74.10	1806	65.79	2845	67.27	4050	66.88	2199	66.68	3355	73.61
	1 = Injured	755	19.52	688	25.06	1037	24.52	1487	24.55	824	24.98	908	19.92
	2 = Killed	247	6.39	251	9.14	347	8.21	519	8.57	275	8.34	295	6.47
Vehicle speed	0 (More than 50 mph)	127	3.41	46	1.73	107	2.63	127	2.18	65	2.04	103	2.33
	1 (Less than 50 mph)	3601	96.59	2608	98.27	3967	97.37	5703	97.82	3118	97.96	4323	97.67
Visibility	1 (Dawn)	261	6.37	287	10.08	30	0.69	39	0.62	24	0.69	46	0.94
	2 (Dusk)	25	0.61	24	0.84	24	0.55	68	1.08	377	10.86	325	6.64
	3 (Dark)	3256	79.49	245	8.60	252	5.79	394	6.27	596	17.18	3467	70.78
	4 (Day)	554	13.53	2292	80.48	4045	92.97	5779	92.02	2473	71.27	1060	21.64
Weather	1 (Cloudy)	842	20.56	552	19.38	895	20.57	1269	20.21	677	19.51	917	18.72
	2 (Rain)	388	9.47	173	6.07	235	5.40	315	5.02	173	4.99	404	8.25
	3 (Fog)	152	3.71	85	2.98	38	0.87	26	0.41	17	0.49	63	1.29
	4 (Sleet)	20	0.49	8	0.28	10	0.23	16	0.25	2	0.06	12	0.24
	5 (Snow)	113	2.76	71	2.49	116	2.67	140	2.23	71	2.05	157	3.21
	6 (Clear)	2581	63.01	1959	68.79	3057	70.26	4514	71.88	2530	72.91	3345	68.29
Train speed	0 (More than 50 mph)	531	13.74	486	17.24	625	14.49	830	13.34	573	16.70	694	14.76
	1 (Less than 50 mph)	3335	86.26	2333	82.76	3689	85.51	5394	86.66	2859	83.30	4009	85.24
Vehicle type	1 (Truck)	441	13.09	970	34.59	1492	37.05	1367	33.42	1031	26.27	735	14.76
	2 (Pick-up truck)	518	15.38	494	17.62	706	17.53	750	18.34	768	19.57	915	18.37
	3 (Van)	159	4.72	108	3.85	183	4.54	194	4.74	193	4.92	232	4.66
	4 (Bus)	6	0.18	6	0.21	3	0.07	6	0.15	11	0.28	8	0.16
	5 (Motorcycle)	14	0.42	4	0.14	14	0.35	13	0.32	15	0.38	24	0.48
	6 (Auto)	2230	66.21	1222	43.58	1629	40.45	1760	43.03	1907	48.59	3067	61.57
Control device	0 (Active control)	2956	72.68	1683	59.58	2338	54.35	3449	55.48	2089	60.73	3257	66.88
	1 (Passive control)	1111	27.32	1142	40.42	1964	45.65	2768	44.52	1351	39.27	1613	33.12
Driver's age	1 (Less than 25)	1073	31.16	592	23.27	639	16.57	891	16.78	532	18.63	726	19.52
	2 (25–29)	502	14.58	274	10.77	349	9.05	427	8.04	227	7.95	353	9.49
	3 (30–49)	1375	39.92	1025	40.29	1565	40.58	2094	39.44	1130	39.57	1492	40.12
	4 (50–69)	424	12.31	507	19.93	891	23.10	1343	25.29	719	25.18	875	23.53
	5 (70 and above)	70	2.03	146	5.74	413	10.71	555	10.45	248	8.68	273	7.34
Gender	0 (Male)	2948	76.93	2071	72.50	4085	76.60	4639	76.64	2483	74.83	3310	73.62
	1 (Female)	884	23.07	711	27.30	1232	23.10	1414	23.36	835	25.17	1186	26.38
Area type	0 (Open space)	2552	24.20	2552	74.44	3314	78.14	1711	31.18	914	29.47	1115	24.87
	1 (Other areas)	7995	75.80	7995	25.56	927	21.86	3777	68.82	2187	70.53	3369	75.13
Roadway pavement	0 (Non-paved)	371	9.91	431	17.23	693	18.55	981	17.83	484	15.58	487	10.84
	1 (Paved)	3374	90.09	2070	82.77	3043	81.45	4521	82.17	2623	84.42	4004	89.16
AADT	0 (More than 10,000)	690	18.63	326	13.25	438	11.93	690	12.78	467	15.21	731	16.48
	1 (Less than 10,000)	3014	81.37	2134	86.75	3232	88.07	4709	87.22	2603	84.79	3704	83.52

with zero mean and unit variance for the ordered probit model. In addition, the error terms for different outcomes are assumed to be uncorrelated.

The dependent variable in this study, Y, is coded as 1, 2, ⋯, J, and is defined in Eq. (2):

$$Y = \begin{cases} 1 & -\infty \le y_i^* < \tau_1 \\ j & \tau_{j-1} \le y_i^* < \tau_j \\ J & \tau_{J-1} \le \infty \end{cases} \tag{2}$$

where J is the number of driver injury levels, τ_j is the threshold value to be estimated for each level. The ordered probit model in Eq. (3) provides the probabilities of y_i^* taking on each of values ($j = 1, \cdots, J$).

$$\left.\begin{array}{l} P(y_i^* = 1) = \Phi(\tau_1 - X_i\beta) \\ P(y_i^* = j) = \Phi(\tau_j - X_i\beta) - \Phi(\tau_{j-1} - X_i\beta) \\ P(y_i^* = J) = 1 - \Phi(\tau_{J-1} - X_i\beta) \end{array}\right\} \tag{3}$$

where $\Phi(\cdot)$ is the cumulative probability function of a normal distribution, $P(y_i^* = j)$ is the probability of response variable taking a specific severity level j. In our case, y_i is chosen as the injury severity, which is grouped into three categories including no-injury, injury, and death.

The parameters of the ordered probit model are estimated using a maximum likelihood estimation method which involves the systematic evaluation of the function at different points to find the point at which the function can be maximized. The log likelihood function in Eq. (4) is the sum of the individual log probabilities (L).

$$L = \sum_{i=1}^{n}\sum_{j=1}^{3} \log\left[\Phi(\tau_j - X_i\beta) - \Phi(\tau_{j-1} - X_i\beta)\right] \tag{4}$$

Marginal effects are estimated in the ordered probit model to get the impacts of variables on the probability of each injury severity level (Zhang et al., 2011). For continuous variables, the marginal effect of a variable on injury severity can be determined by Eq. (5).

$$P(Y = i)/\partial X = [\phi(\mu_{i-1} - \beta X) - \phi(\mu_i - \beta X)]\beta \tag{5}$$

where $\phi(\cdot)$ is the standard normal density, X is continuous variable, μ is the threshold value to be estimated for each level.

For binary variables, the marginal effect of a variable on injury severity can be determined by Eq. (6) and the outcome when the variable is equal to one is compared with that when the variable is zero, while all other variables remain constant.

$$\Delta(Y = i/x_n) = \Pr(Y = i/x_n = 1) - \Pr(Y = i/x_n = 0) \tag{6}$$

where x_n is binary variable, $\Delta(\cdot)$ is the marginal effect of a variable on injury severity for binary variable.

2.3. *Statistical tests*

To determine whether significant differences existed between parameter estimates in different time periods, likelihood ratio tests were performed as was done in previous studies (Islam and Mannering, 2006; Morgan and Mannering, 2011). $LL(\beta_T)$ estimates a model on all data (all time period groups being tested) and then $\sum_G LL(\beta_g)$ estimates separate models for each individual time period group. The six time periods being tested include: 1) early morning; 2) a.m. peak; 3) a.m. off-peak; 4) p.m. off-peak; 5) p.m. peak; 6) evening. The test statistic is as below

$$X^2 = -2\left[LL(\beta_T) - \sum_G LL(\beta_g)\right] \tag{7}$$

where $LL(\beta_T)$ is the model's log-likelihood at convergence of the model estimate using data for the entire day, $LL(\beta_g)$ is the log-likelihood at convergence of the model estimate using data for time period group, and g and G is the set of all time period groups. This statistic X^2 is χ^2, which is distributed with degrees of freedom and equal to the summation of estimated coefficients in the subset-data models minus the number of estimated coefficients in the total-data models.

The second version of the test is used to compare two individual time period groups. The test statistic is as follow

$$X^2 = -2[LL(\beta_{AB}) - LL(\beta_B)] \tag{8}$$

where $LL(\beta_{AB})$ is the model log-likelihood using group B's data and group A's estimated coefficients (the coefficients at convergence of a model estimate on group A's data), $LL(\beta_B)$ is the log-likelihood at convergence using group B's data and group B's converged coefficients. This also can be reversed so that group A's data is used with group B's estimated coefficients. In this test, the statistic is again χ^2, which is distributed with degrees of freedom and equal to the number of estimated coefficients.

3. Results

As described in the previous section, a likelihood ratio test is performed to determine whether significant differences existed between parameter estimates in six time periods including: 1) early morning; 2) a.m. peak; 3) a.m. off-peak; 4) p.m. off-peak; 5) p.m. peak; 6) evening. For differences between time periods, all tests indicate that the hypothesis that time-of-day models are equal and can be rejected with over 99.5% confidence. These tests include comparing combined time-of-day models with separate time-of-day models (Eq. (7)) and comparing two individual time-of-day models (Eq. (8)). The combination of these two tests yields an excellent assessment of the statistical differences between different time periods. Therefore, separate time-of-day models are developed.

3.1. *Model estimation results*

Based on the statistical tests above, six ordered probit models are estimated using the Limdep software package to analyze the injury levels for drivers involved in highway-rail grade crossing crashes in six time periods. These models examine the effects of explanatory variables on the dependent variable, which is driver injury level. A positive sign for an estimated parameter implies a higher probability of injury severity for highway vehicle drivers as the value of the explanatory variable increases. The significance of the independent variables with a p-value <0.05 is also provided. Detailed model estimation results are presented in Tables 2–7.

As estimated using the ordered probit model, the increase in both highway vehicle speed and train speed will significantly increase the level of injury severity given that crashes happen, especially for crashes during the early morning period. This can be seen in Table 2 which shows the estimates for the early morning period. The estimated coefficients are 0.782 for vehicle speed and 0.792 for train speed, which are larger than the coefficients in other time periods. Bad weather conditions (snow, rain, and sleet) and bad visibility (dark and dusk) can deadly cause high injury severity level especially during the a.m. peak and p.m. peak. Drivers are more likely to have high level injury severity in an open space area during the p.m. off-peak, during which the coefficient estimate is 0.081, higher than other time periods. High level injury severity crashes are more likely to occur on non-paved roadways, especially during peak hours, which can be seen in Table 3 where the coefficient estimate is 0.075 for the a.m. peak and Table 6 where the coefficient estimate is 0.059 for p.m. peak. Regarding the effect of driver's age, the typical early morning crash drivers are in the age groups of “less than 25” and “25 to 29”. The coefficient estimates are 0.528 for “less than 25” age group and 0.292 for “25 to 29” age group which are larger than other age group coefficient estimates. Typical drivers in peak hour crashes are the age groups of “25 to 29” and “30 to 49”. During the a.m. peak, the coefficient estimates are 0.371 for “25 to 29” age group and

Table 2 – Model results for early morning.

Variable description	Parameter estimate	p-value	Marginal effect		
Vehicle speed		0.008			
Veh. Spd > 50 mph	0.782	0.008	−0.2897	0.1221	0.1676
Veh. Spd < 50 mph	–	–	–	–	–
Visibility		0.026			
Dawn	0.239	0.046	−0.0679	0.0401	0.0278
Dusk	0.298	0.528	−0.0735	0.0408	0.0327
Dark	0.571	0.035	−0.0789	0.0368	0.0421
Day	–	–	–	–	–
Weather condition		0.021			
Cloudy	0.087	0.038	−0.0682	0.0253	0.0429
Rain	0.124	0.016	−0.0501	0.0172	0.0329
Fog	0.207	0.033	−0.0371	0.0213	0.0158
Sleet	0.351	0.028	−0.0520	0.0351	0.0169
Snow	0.123	0.037	−0.0457	0.0294	0.0163
Clear	–	–	–	–	–
Train speed		0.023			
Train Spd > 50 mph	0.792	0.023	−0.2648	0.1225	0.1423
Train Spd < 50 mph	–	–	–	–	–
Vehicle type		0.029			
Truck	−0.032	0.026	0.0070	−0.0050	−0.0020
Pick-up truck	0.265	0.018	−0.0110	0.0090	0.0020
Van	0.318	0.029	−0.0030	0.0020	0.0010
Bus	0.421	0.031	0.0060	−0.0040	−0.0020
Motorcycle	0.536	0.042	−0.0130	0.0090	0.0040
Auto	–	–	–	–	–
Control device		0.002			
Active control	0.131	0.002	−0.0210	0.0150	0.0060
Passive control	–	–	–	–	–
Driver's age		0.035			
Less than 25	0.528	0.021	−0.0250	0.0167	0.0083
25 to 29	0.292	0.039	−0.0132	0.0097	0.0035
30 to 49	0.382	0.052	−0.0066	0.0013	0.0053
50 to 69	0.211	0.219	−0.0160	0.0125	0.0035
Over 70	–	–	–	–	–
Area type		0.018			
Open space	0.019	0.018	−0.0045	0.0027	0.0018
Other area	–	–	–	–	–
Pavement type		0.021			
Non-paved	0.045	0.021	−0.0636	0.0316	0.0532
Paved	–	–	–	–	–
Traffic volume		0.043			
More than 10,000	0.128	0.043	−0.0546	0.0125	0.0421
Less than 10,000	–	–	–	–	–
No. of Obs.	3868				
Log likelihood	−681				
Pseudo R-squared	0.021				
p-value	0				

Table 3 – Model results for a.m. peak.

Variable description	Parameter	*p*-value	Marginal effect		
Vehicle speed		0.044			
Veh. Spd > 50 mph	0.609	0.044	−0.2551	0.1026	0.1525
Veh. Spd < 50 mph	–	–	–	–	–
Visibility		0.029			
Dawn	0.226	0.003	−0.0310	0.0180	0.0130
Dusk	0.365	0.036	−0.0130	0.0080	0.0050
Dark	0.852	0.027	−0.0430	0.0120	0.0310
Day	–	–	–	–	–
Weather condition		0.025			
Cloudy	0.352	0.019	−0.0875	0.0312	0.0563
Rain	0.294	0.009	−0.0687	0.0216	0.0471
Fog	0.172	0.027	−0.0145	0.0019	0.0126
Sleet	0.692	0.035	−0.0305	0.0123	0.0182
Snow	0.356	0.028	−0.0475	0.0183	0.0292
Clear	–	–	–	–	–
Train speed		0.028			
Train Spd > 50 mph	0.597	0.028	−0.2333	0.1012	0.1321
Train Spd < 50 mph	–	–	–	–	–
Vehicle type		0.021			
Truck	−0.045	0.017	0.0080	−0.0050	−0.0030
Pick-up truck	0.268	0.021	−0.0090	0.0070	0.0020
Van	0.321	0.018	−0.0040	0.0020	0.0020
Bus	0.426	0.025	0.0070	−0.0040	−0.0030
Motorcycle	0.561	0.031	−0.0120	0.0070	0.0050
Auto	–	–	–	–	–
Control device		0.005			
Active control	0.145	0.005	−0.0190	0.0120	0.0070
Passive control	–	–	–	–	–
Driver's age		0.031			
Less than 25	0.421	0.045	−0.0251	0.0067	0.0184
25 to 29	0.371	0.021	−0.0172	0.0037	0.0135
30 to 49	0.081	0.019	−0.0106	0.0013	0.0093
50 to 69	0.133	0.053	−0.0136	0.0127	0.0009
Over 70	–	–	–	–	–
Area type		0.003			
Open space	0.052	0.003	−0.0149	0.0021	0.0128
Other area	–	–	–	–	–
Pavement type		0.005			
Non-paved	0.075	0.005	−0.0644	0.0213	0.0431
Paved	–	–	–	–	–
Traffic volume		0.009			
More than 10,000	0.463	0.009	−0.0933	0.0212	0.0721
Less than 10,000	–	–	–	–	–
No. of Obs.	2745				
Log likelihood	−721				
Pseudo *R*-squared	0.016				
p-value	0				

0.081 for “30 to 49” age group. During the p.m. peak, the coefficient estimates are 0.317 for “25 to 29” age group and 0.348 for “30 to 49” age group.

3.2. *Marginal effects analysis*

Marginal effects analysis was also conducted to directly reflect the impact of contributing factors on each of the three types of injury levels which are PDO, injury, and fatality. The marginal effects describe the increase or decrease in the probability of each injury severity level associated with the change of significant independent variables. For categorical variables, the marginal coefficients reflect the change of probability of injury severity compared with the reference categorical variables when all other independent variables remain the same. To keep this study a manageable size and to highlight the important differences between different time periods, an analysis of the two variables, vehicle speed and train speed, having the greatest influence on injury severity level, is presented.

Compared with the probability of a fatality in a highway-rail grade crossing crash occurring when the train speed is less than 50 mph, the probability of a fatality in a highway-rail grade crossing crash at a train speed higher than 50 mph is 14.23% higher in the early morning, 13.21% higher during the a.m. peak and 10.21% higher during the a.m. off-peak. In other time periods, the probability of a fatality is also greater when the train speed exceeds 50 mph than the probability of a

Table 4 – Model results for a.m. off-peak.

Variable description	Parameter	*p*-value	Marginal effect		
Vehicle speed		0.027			
Veh. Spd > 50 mph	0.143	0.027	−0.1449	0.0620	0.0829
Veh. Spd < 50 mph	–	–	–	–	–
Visibility		0.035			
Dawn	0.156	0.037	−0.0210	0.0180	0.0030
Dusk	0.279	0.017	−0.0260	0.0210	0.0050
Dark	1.256	0.176	−0.0410	0.0270	0.0140
Day	–	–	–	–	–
Weather condition		0.042			
Cloudy	0.165	0.009	−0.0565	0.0252	0.0313
Rain	0.252	0.032	−0.0550	0.0231	0.0319
Fog	1.105	0.071	−0.0255	0.0018	0.0237
Sleet	0.653	0.004	−0.0374	0.0123	0.0251
Snow	0.271	0.081	−0.0635	0.0422	0.0213
Clear	–	–	–	–	–
Train speed		0.032			
Train Spd > 50 mph	0.382	0.032	−0.1933	0.0912	0.1021
Train Spd < 50 mph	–	–	–	–	–
Vehicle type		0.029			
Truck	−0.029	0.023	0.0060	−0.0050	−0.0010
Pick-up truck	0.275	0.008	−0.0150	0.0110	0.0040
Van	0.321	0.023	−0.0020	0.0010	0.0010
Bus	0.416	0.027	0.0050	−0.0030	−0.0020
Motorcycle	0.432	0.034	−0.0160	0.0110	0.0050
Auto	–	–	–	–	–
Control device		0.005			
Active control	0.107	0.005	−0.0240	0.0180	0.0060
Passive control	–	–	–	–	–
Driver's age		0.031			
Less than 25	0.086	0.033	−0.0062	0.0033	0.0029
25 to 29	0.181	0.046	−0.0133	0.0061	0.0072
30 to 49	0.052	0.013	−0.0161	0.0069	0.0092
50 to 69	0.023	0.041	−0.0158	0.0075	0.0083
Over 70	–	–	–	–	–
Area type		0.016			
Open space	0.025	0.016	−0.0029	0.0021	0.0008
Other area	–	–	–	–	–
Pavement type		0.009			
Non-paved	0.022	0.009	−0.0373	0.0251	0.0122
Paved	–	–	–	–	–
Traffic volume		0.035			
More than 10,000	0.391	0.035	−0.0393	0.0162	0.0231
Less than 10,000	–	–	–	–	–
No. of Obs.	4299				
Log likelihood	−756				
Pseudo *R*-squared	0.013				
p-value	0				

fatality when it is less than 50 mph (12.12% higher during the p.m. off-peak, 11.25% higher during the p.m. peak, and 10.31% in the evening.

Vehicle speed has a similar effect on the probability of a fatality as train speed. When the vehicle speed exceeds 50 mph, the probability of a fatality is 16.76% higher in the early morning, 15.25% higher during the a.m. peak and 8.29% higher during the a.m. off-peak than the probability of a fatality when the vehicle speed is less than 50 mph. In other time periods, the probability of a fatality is 13.34% higher during the p.m. off-peak, 13.24% higher during the p.m. peak, and 11.26% higher in the evening when the vehicle speed exceeds 50 mph, than the probability of a fatality when the vehicle speed is less than 50 mph.

4. Model discussion

Regarding the specific findings, many instances of significant differences in different time periods are observed. Possible countermeasures and intervention points are discussed below.

As to vehicle speed, the results show that there is an increased likelihood of higher injury severities in highway-rail crossing crashes happening with vehicle speeds greater than 50 mph. The impact of vehicle speed on injury severity can be explained by the fact that the increased vehicle speed will result in the inability of drivers to visually detect an on-coming train, thereby increasing the likelihood of a higher injury

Table 5 – Model results for p.m. off-peak.

Variable description	Parameter	*p*-value	Marginal effect		
Vehicle speed		0.032			
Veh. Spd > 50 mph	0.312	0.032	−0.2187	0.0853	0.1334
Veh. Spd < 50 mph	–	–	–	–	–
Visibility		0.035			
Dawn	0.259	0.028	−0.0190	0.0150	0.0040
Dusk	1.783	0.037	−0.0330	0.0280	0.0050
Dark	0.918	0.047	−0.0630	0.0350	0.0280
Day	–	–	–	–	–
Weather condition		0.039			
Cloudy	0.288	0.037	−0.0443	0.0125	0.0318
Rain	0.159	0.031	−0.0395	0.0213	0.0182
Fog	0.213	0.042	−0.0365	0.0213	0.0152
Sleet	0.215	0.032	−0.0385	0.0172	0.0213
Snow	0.432	0.015	−0.0535	0.0322	0.0213
Clear	–	–	–	–	–
Train speed		0.041			
Train Spd > 50 mph	0.383	0.041	−0.2083	0.0871	0.1212
Train Spd < 50 mph	–	–	–	–	–
Vehicle type		0.025			
Truck	−0.025	0.017	0.0060	−0.0050	−0.0010
Pick-up truck	0.216	0.013	−0.0110	0.0090	0.0020
Van	0.307	0.021	−0.0030	0.0020	0.0010
Bus	0.352	0.023	0.0070	−0.0050	−0.0020
Motorcycle	0.427	0.031	−0.0140	0.0090	0.0050
Auto	–	–	–	–	–
Control device		0.003			
Active control	0.115	0.003	−0.0230	0.0170	0.0060
Passive control	–	–	–	–	–
Driver's age		0.035			
Less than 25	0.082	0.029	−0.0102	0.0015	0.0087
25 to 29	0.171	0.062	−0.0088	0.0031	0.0057
30 to 49	0.076	0.027	−0.0111	0.0019	0.0092
50 to 69	0.031	0.017	−0.0049	0.0028	0.0021
Over 70	–	–	–	–	–
Area type		0.029			
Open space	0.081	0.029	−0.0036	0.0027	0.0009
Other area	–	–	–	–	–
Pavement type		0.019			
Non-paved	0.031	0.019	−0.0432	0.0281	0.0151
Paved	–	–	–	–	–
Traffic volume		0.001			
More than 10,000	0.293	0.001	−0.0412	0.0284	0.0128
Less than 10,000	–	–	–	–	–
No. of Obs.	6056				
Log likelihood	−827				
Pseudo *R*-squared	0.038				
p-value	0				

severity when they collide with a train. For crashes occurring in the early morning, drivers tend to drive faster and their reaction times are slower due to lack of enough sleep in this situation. During the a.m. peak, drivers are more likely to drive faster to avoid being late to work. Similarly, during the p.m. peak, drivers tend to drive faster to get home sooner and they may be tired and with slower reaction times after a long day at work. During the p.m. off-peak, drivers may feel tired with slower reaction times after lunch. All in all, there is a strong association between high vehicle speed and higher crash severities (Haleem and Abdel-Aty, 2010; Hao and Daniel, 2014).

Train speed has a similar affection on injury severity. A higher train speed means less reaction times for motor vehicle drivers. Crashes occurring in the early morning have the highest injury severity, as shown in Table 2, followed by a.m. peak, p.m. peak, p.m. off-peak, evening, and a.m. off-peak. In the early morning, drivers tend to drive faster without stopping when they go through highway-rail grade crossing intersections due to the low traffic volume at that time. If the train speed is higher at this time, motor vehicle drivers are less likely to detect a train entering the crossing. For peak hour crashes, drivers are most likely to pass through highway-rail grade crossing intersections without stopping due to their hurry to go to work during the a.m. peak or go home during the p.m. peak. There is an increased likelihood of higher injury severities in highway-rail crossing crashes when the train speed is more than 50 mph (Hao and Daniel, 2013; Milton et al., 2008). As a consequence, a reduction in

Table 6 – Model results for p.m. peak.

Variable description	Parameter	*p*-value	Marginal effect		
Vehicle speed		0.022			
Veh. Spd > 50 mph	0.521	0.022	−0.1747	0.0423	0.1324
Veh. Spd < 50 mph	–	–	–	–	–
Visibility		0.038			
Dawn	0.321	0.042	−0.0140	0.0130	0.0010
Dusk	0.186	0.031	−0.0220	0.0190	0.0030
Dark	1.112	0.035	−0.0380	0.0210	0.0170
Day	–	–	–	–	–
Weather condition		0.027			
Cloudy	0.505	0.021	−0.0553	0.0126	0.0427
Rain	0.213	0.031	−0.0404	0.0185	0.0219
Fog	0.276	0.025	−0.0261	0.0152	0.0109
Sleet	0.388	0.132	−0.0338	0.0121	0.0217
Snow	0.321	0.009	−0.0433	0.0271	0.0162
Clear	–	–	–	–	–
Train speed		0.036			
Train Spd > 50 mph	0.614	0.036	−0.2101	0.0976	0.1125
Train Spd < 50 mph	–	–	–	–	–
Vehicle type		0.028			
Truck	−0.049	0.018	0.0110	−0.0080	−0.0030
Pick-up truck	0.287	0.013	−0.0110	0.0090	0.0020
Van	0.338	0.018	−0.0030	0.0020	0.0010
Bus	0.452	0.025	0.0110	−0.0080	−0.0030
Motorcycle	0.621	0.032	−0.0210	0.0140	0.0070
Auto	–	–	–	–	–
Control device		0.005			
Active control	0.136	0.005	−0.0240	0.0150	0.0090
Passive control	–	–	–	–	–
Driver's age		0.028			
Less than 25	0.217	0.041	−0.0402	0.0181	0.0221
25 to 29	0.317	0.021	−0.0278	0.0216	0.0062
30 to 49	0.348	0.003	−0.0066	0.0013	0.0053
50 to 69	0.058	0.034	−0.0191	0.0077	0.0114
Over 70	–	–	–	–	–
Area type		0.033			
Open space	0.081	0.033	−0.0048	0.0019	0.0029
Other area	–	–	–	–	–
Pavement type		0.002			
Non-paved	0.059	0.002	−0.0549	0.0152	0.0397
Paved	–	–	–	–	–
Traffic volume		0.032			
More than 10,000	0.391	0.032	−0.1038	0.0381	0.0657
Less than 10,000	–	–	–	–	–
No. of Obs.	3298				
Log likelihood	−931				
Pseudo *R*-squared	0.025				
p-value	0				

vehicle speed and train speed at highway-rail grade crossings is a policy that can be particularly effective in moderating injury severity, as it allows more reaction times for last-minute maneuvering and braking.

As to the visibility, there is an increased likelihood of higher injury severities in highway-rail crossing crashes when the visibility is poor. During the a.m. peak, drivers are 1.3% more likely to be killed and are more likely to suffer severe injuries in a crash at dawn than during the day as shown in Table 3. During the p.m. peak, drivers are 1.7% more likely to be killed and are more likely to have severe injuries in a crash occurring in the dark than during the day. Drivers will sustain higher severity injuries during evening and early morning as a result of darkness as well. Bad visibility conditions influence driver's injury severity while good light conditions decrease the probability of severe injury (Abdel-Aty et al., 2011; McCollister and Pflaum, 2007; Zhang et al., 2011).

The modeling results suggest that bad weather conditions (sleet, snow, fog, rain, and cloudy) are deadly for motor vehicle drivers. Cloudiness, snow, and rain have a considerable influence on crashes occurring in the early morning and evening, and fog has a similar influence on crashes occurring during peak hours (a.m. peak or p.m. peak). In the early morning, cloudiness snow, and rain increase the probability of a fatality by 4.29%, 1.69% and 3.29%, respectively. As shown in Table 2, drivers tend to drive faster (over 50 mph) in the morning most likely due to the low traffic volumes. In addition, it is harder for drivers to stop under sleet, snow, and rain

Table 7 – Model results for evening.

Variable description	Parameter	p-value	Marginal effect		
Vehicle speed		0.016			
Veh. Spd > 50 mph	0.267	0.016	−0.1687	0.0561	0.1126
Veh. Spd < 50 mph	–	–	–	–	–
Visibility		0.025			
Dawn	0.198	0.019	−0.0273	0.0252	0.0021
Dusk	1.123	0.039	−0.0383	0.0251	0.0132
Dark	0.726	0.021	−0.0665	0.0393	0.0272
Day	–	–	–	–	–
Weather condition		0.028			
Cloudy	0.221	0.022	−0.0339	0.0212	0.0127
Rain	0.328	0.031	−0.0455	0.0127	0.0328
Fog	0.305	0.044	−0.0396	0.0233	0.0163
Sleet	0.287	0.031	−0.0636	0.0321	0.0315
Snow	0.399	0.042	−0.0653	0.0392	0.0261
Clear	–	–	–	–	–
Train speed		0.046			
Train Spd > 50 mph	0.478	0.046	−0.1909	0.0878	0.1031
Train Spd < 50 mph	–	–	–	–	–
Vehicle type		0.023			
Truck	−0.026	0.018	0.0070	−0.0050	−0.0020
Pick-up truck	0.224	0.015	−0.0090	0.0080	0.0010
Van	0.287	0.021	−0.0030	0.0010	0.0020
Bus	0.356	0.025	0.0060	−0.0050	−0.0010
Motorcycle	0.521	0.035	−0.0160	0.0110	0.0050
Auto	–	–	–	–	–
Control device		0.006			
Active control	0.116	0.006	−0.0230	0.0170	0.0060
Passive control	–	–	–	–	–
Driver's age		0.029			
Less than 25	0.021	0.038	−0.0272	0.0181	0.0091
25 to 29	0.502	0.031	−0.0092	0.0038	0.0054
30 to 49	0.261	0.003	−0.0051	0.0028	0.0023
50 to 69	0.168	0.517	−0.0035	0.0017	0.0018
Over 70	–	–	–	–	–
Area type		0.029			
Open space	0.043	0.029	−0.0049	0.0041	0.0008
Other area	–	–	–	–	–
Pavement type		0.032			
Non-paved	0.012	0.032	−0.0429	0.0138	0.0291
Paved	–	–	–	–	–
Traffic volume		0.035			
More than 10,000	0.294	0.035	−0.0459	0.0321	0.0138
Less than 10,000	–	–	–	–	–
No. of Obs.	4558				
Log likelihood	−871				
Pseudo R-squared	0.015				
p-value	0				

conditions due to the lower friction forces when a crash occurs, which is more likely to result in high level injury severity. During the peak hours, as shown in Tables 3 and 6, vehicle speed is higher due to drivers hurry to work during the a.m. peak and rushing home during the p.m. peak. If fog occurs during the peak hours, drivers will sustain higher level injury severities in crashes due to bad visibility. Bad weather makes roads less skid resistant, resulting in reducing the drivers' braking and steering capabilities, and worse collision angles, which lead to more severe injuries (Kilpelainen and Summala, 2007; Kim et al., 2007). The limitations in visibility and the ability for drivers to slow or stop before the rail crossings as a result of bad weather cause high level injury severity.

Regarding to traffic control device, there is an increased likelihood of higher injury severity crashes occurring at highway-rail crossing with passive control. During the a.m. peak, drivers have a probability of being killed of 0.7% and are more likely to suffer severe injuries at crossings with passive controls compared with crossings with active control, as shown in Table 3. Similarly, during the p.m. peak, drivers have a probability of being killed of 0.9% and are more likely to suffer severe injuries at a crossing with passive control compared with crossings with active control. An explanation from Pai and Saleh (2007) for this interesting result is that, while passive control might act as a deterrent to speed, vehicle drivers might drive more recklessly at passive control highway-rail grade crossings.

As expected, driver's injury severity by time of day differs in different age groups. Typically, drivers involved in early morning crashes are in the "less than 25" and "25 to 29" age groups and those involved in peak hour crashes are in the "25 to 29" and "30 to 49" age groups. Drivers who sustain severe injuries in crashes during the a.m. and p.m. off-peaks tend to be older, while drivers involved in crashes in the evening tend to be in the "30 to 49" age group. In the early morning, drivers involved in crashes tend to young people leaving bars or clubs. The increased probability of being killed in crashes occurring in this time period may be due to slow reaction times as a result of sleepiness. Young drivers seem to be more susceptible to sleepiness and more often involved in sleep-related crashes (Otmani et al., 2005; Raub, 2006). During the peak hours, they are typically workers in the "25 to 29" and "30 to 49" age groups. As mentioned above, drivers are more likely to drive faster to avoid being late to work in the a.m. peak. Similarly, during the p.m. peak, they tend to drive faster to get home sooner and they may be tired after a long day at work and have slower reaction times.

The results also suggest that the area type is an important factor on driver's injury severity level. Drivers in open space areas are more likely to have severe injuries with a probability of being killed of 0.18% in the early morning, 1.28% during the a.m. peak and 0.29% during the p.m. peak compared with other time periods. This can be explained by the fact that, in the early morning, vehicle drivers may drive more recklessly through highway-rail grade crossings in open space areas compared with other areas. During the peak hours, they are more likely to drive without reducing speed in open space areas. Open space areas are associated with higher crash severity levels due to higher speed and lack of medical facilities (Tay et al., 2011; Theofilatos and Yannis, 2014).

The increased probability of being killed in accidents on non-paved roadways is highest during the peak hours, followed by the early morning, the p.m. off-peak, the a.m. off-peak, and the evening. As mentioned above, drivers tend to drive faster to work during a.m. peak and get back home sooner after work. In the early morning, drivers tend to drive faster due to low traffic volumes. Non-paved roadways have a lower friction force, therefore drivers need much more time to stop. As a result, paving unpaved roadways can be particularly effective in moderating injury severity.

High traffic volumes are strongly associated with "a.m. peak", "p.m. off-peak" and "p.m. peak" crashes. High traffic volumes during peak hours can result in traffic jams, which make drivers feel anxious and lose their temper. Crashes occurring during the p.m. off-peak may to be due to sleepiness after lunch and slower reaction times. High traffic volumes are associated with higher crash severity due to anxiety, sleepiness, and lack of patience (Hao and Daniel, 2013; Ulfarsson and Mannering, 2004).

5. Conclusions

This paper examines the driver's injury severity at highway-rail grade crossings in different time of day periods. The study is motivated by the fact that vehicle driver's injury level at highway-rail grade crossings during the a.m. peak, p.m. peak, and p.m. off-peak is considerably higher than other time periods. In addition, there is no published time of day model analysis of driver's injury level at highway-rail grade crossings. In this study, a model estimation is conducted to evaluate the differences in different times of day and the estimation results for the different models are compared. From these findings, it can be found that it is inappropriate to estimate a single model for the entire day. The estimation results show there are significant differences in different time periods with regard to how various factors affect injury severity at highway-rail grade crossings. The findings offer insights into measures which can be undertaken to reduce driver's injury level in specific time periods. The conclusions for six time periods are summarized as below.

(1) Early morning

The typical drivers involved in crashes in the early morning are in the "less than 25" and "25 to 29" age groups. "Sleet" is the most dangerous weather condition. Motor vehicle drivers tend to drive faster in the early morning. Therefore, speed control for both vehicles and trains will significantly reduce driver's injury level. In addition, fatal and sever injuries tend to occur in crashes at highway-rail grade crossings located in open space areas with non-paved roadways. These conditions tend to result in lower traffic volumes which may encourage drivers to drive faster, which means they need more time to stop.

(2) a.m. peak

The typical drivers involved in crashes during the a.m. peak are in the "25 to 29" and "30 to 49" age groups. The most dangerous weather condition is fog. High traffic volumes can result in traffic jams, which make vehicle drivers anxious and impatient. Therefore, strict traffic laws that prohibit motor vehicle drivers from passing through highway-rail grade crossings without stopping will significantly reduce driver's injury severity.

(3) a.m. off-peak

The typical drivers involved in crashes in the a.m. off-peak are in the "50 to 69" and "70 and above" age groups. Crashes are associated with physiological factors associated with advanced age. Human factors represent the cause of high level injury severity in crashes occurring in this time period. Paving unpaved roadways will greatly help to reduce driver's injury level.

(4) p.m. off-peak

p.m. off-peak is a dangerous period for every age group. Crashes occurring in this time period are mainly caused by sleepiness after lunch time. Drivers tend to feel tired after lunch with slower reaction times. Besides, higher driving speed increases the danger of a crash. Therefore, greater speed control for motor vehicle and education to help them realize the danger of crashes in this time period will significantly reduce driver's injury level.

(5) p.m. peak

The crash characteristics during the p.m. peak are similar to those during the a.m. peak. The typical drivers involved in crashes in the p.m. peak are in the "25 to 29" and "30 to 49" age groups. Human factors are often causes of crashes. Drivers tend to feel tired and have slower reaction times after a long day at work. The high traffic volumes during this period tend to make them feel anxious and impatient which increases the level of injury severity.

(6) Evening

The typical drivers in evening crashes are also in the "25 to 29" and "30 to 49" age groups. They are mainly professional drivers who work overtime or are engaged in social activities after work, which means that they tend to be very tired and sleepy. As a result, their reaction times are slower and thus crashes occurring during this time period tend to result in high level injury severity.

The ultimate goal of this study is to provide a scientific basis for analyzing driver injury severity in different times of day and to develop measures that can potentially reduce driver's injury severity. Future studies should overcome the data limitations in this study. The primary data source used in this study is the FRA database data file from 2002 to 2011 which covers a total of 10 years of highway-rail grade crossing crash data. The characteristics of drivers included in this database are only the drivers' age and gender but the vehicles' age and crashworthiness are not included. To better capture impacts of drivers' behaviors on the injury severity, future studies can include more driver related factors such as driver's height, weight, body structure, alcohol use, and education level. In general, a comprehensive analysis of driver's biomechanics and behavioral responses is strongly recommended for future researches. In addition, comprehensive geometric information (i.e., crossing angle) of crash sites and vegetation clearance in the driving safety triangle are also strongly recommended to be considered for future researches. For the model choice, the ordered probit model addresses the problem of independence of irrelevant alternatives (IIA) and ordered discrete data and as a result this model choice was included in this study. However, this model also suffers from the assumption of a normal distribution for all unobserved components of utility. Therefore, a more flexible model, such as an ordered mixed model, is suggested for the future studies.

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