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Motor Vehicle Driver Injury Severity Study at Highway-rail Grade Crossings in the United States

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ABSTRACT:
There are approximately 240,000 highway-rail grade crossings in the United States. These locations have been considered for further study due to the high crash frequencies at these locations. Existing crash models at highway-rail grade crossings can be classified into two categories: accident frequency prediction models; and driver injury severity models. The majority of these studies have, however, focused on predicting accident frequency at highway-rail grade crossings. Few studies have focused on motor vehicle driver injury severities at highway-rail grade crossings. This research has the objective to determine the contributing factors influencing driver’s injury severity at highway-rail grade crossings. The factors found to significantly influence highway driver injury severity includes: whether the crash occurred during the peak hour, weather, visibility, vehicle type, vehicle speed, AADT, train speed, driver’s age, gender, area type and highway pavement. A marginal analysis was also conducted to quantitatively interpret the marginal effects of contributing factors on each severity level for the highway driver.

KEY WORDS:
Highway-rail grade crossings, driver’s injury severity, ordered probit model.
INTRODUCTION

Over the past several decades, great strides have been made in reducing the number of railroad-highway grade crossing collisions due to the efforts of federal, state and local government, the railroads and through organizations such as Operation Lifesaver Inc, a nationwide, non-profit public information program to reduce collisions, injuries and fatalities at highway-rail crossings. With nearly a quarter of a million railroad and highway crossings in the U.S., improving grade crossing safety is an enormous challenge that takes the combined efforts of railroads, public safety officials, and the general public (18).

There are approximately 240,000 highway-rail grade crossings in the United States. Among these crossings, approximately 39 percent are private and the remainder, or 61 percent, are public (7). Various efforts to improve safety have yielded positive results and from 1980 to 2010, the number of grade crossing collisions between trains and highway-users fell by 81 percent; injuries fell by 79 percent; and associated fatalities fell by 69 percent. Between 2000 and 2010, there was a reduction in the number of fatalities at highway-rail grade crossings from 425 (2000) to 256 (2010) (See Figure 1). Although there has been a reduction in the number of collisions, the number of collisions is still high and needs to be further reduced (1).

A. Accidents at highway-rail grade crossings from 2000 to 2010

B. Fatalities at highway-rail grade crossings from 2000 to 2010

Figure 1. Highway-rail Grade Crossings Information

Previous studies on crash modeling at highway-rail grade crossings focused on estimating the relationship between crash frequency and explanatory variables (2, 4, 2, 19, 14, 16, 20). These studies were aimed at exploring the factors which are likely to increase the crash
frequencies at highway-rail grade crossings. Countermeasures to reduce the number of highway-rail grade crossing accidents were also identified.

In recent years, modeling driver’s injury severity at highway-rail grade crossings has received the interest of several researchers \((6, 10, 13, \text{ and } 12)\). Eluru et al. \((6)\) developed a latent class model to identify driver injury severity factors at highway-railway crossings. The dataset used is from the U.S. Federal Railroad Administration highway-rail grade crossing inventory and collision data for 14,532 crossings from 1997 to 2006. The factors which were found to significantly influence injury severity included driver age, time of accident, presence of snow or rain, vehicle role in the crash and motorist action. The study only considered public grade crossings on the main railway line involving only collisions with passenger vehicles. In reality, accidents at private crossings and involving commercial vehicles should be considered in further studies.

Miranda-Moreno et al. \((13)\) modeled and estimated the severity levels of each individual involved in an accident at highway-railway intersections using a multinomial model. A sample of highway-railway intersections in Canada comprising 1773 crossings is considered in the research. The collision database for the period from 1997 to 2004 was included with 941 highway-railway grade crossing collisions. The authors considered the total risk as the product of accident frequency and expected consequence. The severity model variables were limited to trains speed and posted speed limit and neglected to provide many other potential exogenous variables.

Hu et al. \((10)\) used a logit model to investigate key factors for accident severity at railroad grade crossings. Highway-grade crossing collision data were obtained from the railway police and the Taiwan Rail Administration (TRA) at railroad grade crossings in Taiwan from 1995 to 1997. The original dataset included variables describing railway features, highway features, crossing features, traffic control and other variables. It was found that variables such as the number of daily trains, number of daily trucks, and the use of obstacle detection devices had an impact on higher severity accidents. However, traffic control devices and management tools were found to not significantly influence higher severity accidents.

McCollister et al. \((12)\) developed an injury severity model to predict the probability of accidents, injuries and fatalities at highway-railway crossings. A logistic regression method was adopted as the methodology for estimating the probability of a fatality in a highway-grade crossing collision for vehicular occupants. Two databases from Federal Railroad Administration (FRA) were used in estimating the injury severity model. Train speed, number of trains, percent of trucks, traffic/lanes, angle, traffic control devices, area type, and accident history were used as the research variables in estimating crash injury. After model testing, train speed, number of trains, percent of trucks, traffic control devices and accident history were found to be significant variables. The most significant variables were accident history and traffic congestion. The number of night through trains was very significant, but the number of day through trains was less important. The square root of the maximum speed on a section of track is also highly significant. An interesting result showed that trucks are 60 percent less likely to be involved in a rail-highway crossing crash than passenger vehicles.

**OBJECTIVE**

Although previous studies have focused on analyzing driver’s injury severity at highway-rail grade crossings, the research on this issue has been limited. This study aims to develop highway-rail grade crossing driver injury level severity models using a probit model and data from the Federal Railroad Administration (FRA). An ordered probit model is proposed for use as the
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dependent variable (e.g., injury severity) is inherently ordered. Although the outcome is discrete, the multinomial logit models would fail to capture the ordinal nature of the dependent variable. As a result, the ordered probit model is adopted for use. The following provides a description of the data, followed by the model estimation results. A marginal analysis is also provided as a complementary to explain the significant independent variables. The paper concludes with an overall summary of model findings with potential protective strategies and also gives recommendations for future research.

DATA

FRA Data Source
The Federal Railroad Administration (FRA) started an original national highway-rail crossing inventory database on January 1, 1975. The database includes both current and historical records with 80k to 100k crossings updated per year (22). Three sub databases including a highway-rail grade crossing inventory, highway-rail crossing history file and highway-rail crossing accident databases are also classified in the FRA database. The three databases, which are described below, are linked to each other by a common crossing ID number.

The highway-rail grade crossing inventory database includes crossing inventory data reflecting the current state of each crossing with reference attributes. It was used to identify independent factors which reflect crossing-related attributes and train/vehicle traffic patterns. In our database, four types of information are obtained from this database: warning device type, area type, AADT, and percentage of trucks. This data are sourced from the highway-rail crossing inventory.

The Highway-rail crossing history file documents changes in the crossings including reasons why the file was updated and an effective date of the update. In our study, the highway-rail crossing history file was not utilized.

Highway-rail crossing accident data provides a history file of accidents which have happened at the crossings and the correlated surrounding conditions at that time. Six types of factors in our final sample database are sourced from highway-rail crossing accident data file including: time factors (month, hour, and AM&PM); vehicle information (vehicle speed and vehicle type); train information (train speed); weather information (visibility and weather condition); and driver’s information (age, gender, and driver’s injury levels).

The data was substantially cleaned and checked for consistency. Some crossing IDs are missing in the highway-rail crossing inventory but could be found in highway-rail crossing accident data. In this situation, the crossing would not be chosen to be included in the research sample. The overall process of creating the sample database to be used for model estimations comprises the following two steps: (1) highway-rail grade crossing data is extracted from the FRA (8) database; and (2) key variables are reclassified in this research. In the first step, the two databases are linked together through the common ID number. The following provides an example of the second step for the variable warning device class at highway-rail grade crossings.

This variable contains 9 types of control including: no signs or signals; other signs or signals; cross bucks; stop signs; special active warning device; highway traffic signals; flashing lights; all other gates; and four quad gates. The variable is reclassified into three levels: passive control crossings; active control crossings; and no signal control crossings. This classification differs from the highway crossing categories because control devices are often implemented together at
Data Preparation
A careful and detailed data collection is essential to obtain reliable conclusions. The original dataset includes 25,945 highway-rail grade crossing accidents from 2002-2011. Finally, 15,881 highway-rail grade crossing accidents were selected as our final research sample after the dataset was cleaned and checked for consistency. A full description of the important variables will be shown in Table 1.

<table>
<thead>
<tr>
<th>Category</th>
<th>Variables</th>
<th>Description</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable</td>
<td>Injury</td>
<td>0 (Property Damage Only)</td>
<td>10392</td>
<td>65%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (injured)</td>
<td>4037</td>
<td>25%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2 (killed)</td>
<td>1419</td>
<td>9%</td>
</tr>
<tr>
<td>Time Factor</td>
<td>Peak hour</td>
<td>0 (non-peak)</td>
<td>11127</td>
<td>70%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (peak)</td>
<td>4721</td>
<td>30%</td>
</tr>
<tr>
<td>Weather Condition</td>
<td>Weather</td>
<td>0 (unclear)</td>
<td>4934</td>
<td>31%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (clear)</td>
<td>10914</td>
<td>69%</td>
</tr>
<tr>
<td></td>
<td>Visibility</td>
<td>0 (other)</td>
<td>11285</td>
<td>71%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (dark)</td>
<td>4563</td>
<td>29%</td>
</tr>
<tr>
<td>Vehicle &amp; Train Information</td>
<td>Vehicle Type</td>
<td>0 (Truck Related)</td>
<td>4846</td>
<td>30%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (Other)</td>
<td>11001</td>
<td>70%</td>
</tr>
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<td></td>
<td>Vehicle speed</td>
<td>0 (more than 50mph)</td>
<td>269</td>
<td>2%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (Less than 50mph)</td>
<td>15579</td>
<td>98%</td>
</tr>
<tr>
<td></td>
<td>Train speed</td>
<td>0 (more than 50 mph)</td>
<td>1578</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (less than 50mph)</td>
<td>14270</td>
<td>90%</td>
</tr>
<tr>
<td></td>
<td>AADT</td>
<td>0 (more than 10,000)</td>
<td>2073</td>
<td>13%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (Less 10,000)</td>
<td>13775</td>
<td>87%</td>
</tr>
<tr>
<td>Environmental Factors</td>
<td>Open Space</td>
<td>0 (other areas)</td>
<td>11002</td>
<td>69%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (open space)</td>
<td>4846</td>
<td>31%</td>
</tr>
<tr>
<td></td>
<td>Pavement</td>
<td>0 (no-paved)</td>
<td>2286</td>
<td>14%</td>
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<tr>
<td></td>
<td></td>
<td>1 (paved)</td>
<td>13562</td>
<td>85%</td>
</tr>
<tr>
<td>Driver's Information</td>
<td>Age</td>
<td>0 (young drivers)</td>
<td>11494</td>
<td>72%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (older than 50 years)</td>
<td>4354</td>
<td>27%</td>
</tr>
<tr>
<td></td>
<td>Gender</td>
<td>0 (Male)</td>
<td>11735</td>
<td>74%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (Female)</td>
<td>4113</td>
<td>26%</td>
</tr>
</tbody>
</table>

TABLE 1 Description of Highway-Rail Accidents Characteristics for Analysis
Injury severity is the dependent variable which is ranked as 0: property damage only (PDO), 1: injury, and 2: death. The model contains 11 variables as shown in Table 1. The definition of the variables is also recoded in Table 1. The explanatory variables are classified into five groups including “Time factor”, “Weather condition”, “Vehicle and Train Information”, “Environment factors”, and “Driver’s Information” shown in Table 1.

**ORDERED PROBIT MODEL**

**Ordered Probit Model Formula**

The ordered probit model, which models relationships among ranked outcomes, was used to estimate the injury severity in this research. The multinomial logit model was not selected as this model ignores the ordering of the dependent variable. In this study, driver injury severity is the ordered response.

The general specification of the ordered probit model is given by equation (1) by Zhang et al. in 2011 (24):

\[ y_i^* = X_i^T \beta + \varepsilon_i \]

Where, \( X_i \) is a \((K \times 1)\) vector of observed non-random explanatory variables measuring the attributes of accident victim \( i \), \( \beta \) is a \((K \times 1)\) vector of unknown parameters and \( \varepsilon_i \) is a random error term 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, ..., \( J \), defined in equation (2):

\[
Y = \begin{cases} 
1 & \text{if } -\infty \leq y_i^* < \tau_1 \\
 j & \text{if } \tau_{j-1} \leq y_i^* < \tau_j \\
 J & \text{if } \tau_{J-1} \leq y_i^* < \infty 
\end{cases}
\]

Where \( J \) is the number of driver injury levels, and \( \tau_j \) is the threshold value to be estimated for each level. The ordered probit model in equation (3) provides the thresholds which would indicate the various levels of inclination causing driver injury severity. In addition, the probabilities of \( y_i^* \) taking on each of values \( j = 1, ..., J \) are equal to:

\[
P(y_i^* = 1) = \Phi(\tau_1 - X_i^T \beta) \\
P(y_i^* = j) = \Phi(\tau_j - X_i^T \beta) - \Phi(\tau_{j-1} - X_i^T \beta) \\
P(y_i^* = J) = \Phi(\tau_{J-1} - X_i^T \beta)
\]

Where \( \Phi(\cdot) \) is the cumulative probability function of a normal distribution. In our case, \( y_i \) is chosen as the injury severity, which includes three categories: property damage only, injury, and death.
Ordered Probit Model Estimation

The parameters of the ordered probit models 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 could be maximized. The log likelihood function in equation (4) is the sum of the individual log probabilities according to Cameron et al. (3).

\[
L = \sum_{i=1}^{n} \sum_{j=1}^{3} \log(\Phi(\tau_{j} - X_{it}^T \beta) - \Phi(\tau_{j-1} - X_{it}^T \beta))
\]  

(4)

Ordered Probit Model Marginal Effects

Marginal effects are estimated in ordered probit models to determine the impacts of variables on the probability of each injury severity level by Zhang et al. in 2011 (24). For continuous variables, the marginal effect of a variable for injury severity \( i \) could be determined by equation (5):

\[
P(y = i) / \partial X = [\phi(\mu_{i-1} - \beta X) - \phi(\mu_i - \beta X)] \beta
\]  

(5)

Where \( \phi(.) \) is the standard normal density.

For binary variables, the marginal effect of a variable for injury severity \( i \) could be determined by equation (6) by comparing the outcome when the variable takes one value with that when the variable takes a zero value, while all other variables remain constant.

\[
\Delta(Y = i / x_n) = Pr(Y = i / x_n = 1) - Pr(Y = i / x_n = 0)
\]  

(6)

OVERALL MODEL RESULTS

Model Fit Information

The model was fit using Limdep 9.0 economic software package. The results and model fit information are shown in Table 2. The log likelihood value at convergence of the final model is (-1924) and it is significant with a P-value of 0.000.

Estimation Results

A 95 percent confidence interval is used in this study to identify significant variables impacting driver’s injury severity at highway-rail grade crossings. The coefficients for the final models are presented in Table 2. Coefficients for several sets of explanatory variables in the model are estimated, including “Time factor”, “Weather condition”, “Vehicle and Train Information”, “Environment”, and “Driver’s Information”.

In this research, schedule factor, or the time the crash occurred, is categorized into two levels: Peak hour and Off-Peak, with peak hour as the reference category. The schedule factor influence is considered given a crash accident has already occurred. From the model results, the coefficient for off-peak is a negative coefficient at -0.064. The negative coefficient indicates that there is a decreased likelihood of higher severities at highway-rail crossings during an off-peak time when compared to accidents happening during the peak hour.

Weather condition is referred to from two aspects: weather and visibility. In this study, the weather factor is classified into two groups: bad weather (such as cloudy, rain, fog, sleet and snow), and clear weather which is selected as the base category. Bad weather has a positive coefficient value of 0.074 which indicate an increased likelihood of severe accidents during bad weather.
weather condition at highway rail-grade crossings compared to clear weather condition. Abdel-Aty et al. (15) found that bad weather condition makes it difficult for drivers to stop or slow down to make a stop. Second, visibility is classified into “other condition” (such as dawn, day, and dusk) and “dark”. The positive coefficient value of 0.169 for other or non-dark conditions means an increased likelihood of higher severities for accidents during the other condition. In addition, Zhang et.al (24) found that good light conditions and good weather condition will decrease the probability of severe injuries. The results of this paper show slight differences to what was found by Zhang. The results show that higher severity injuries occurred at highway-rail grade crossings during bad weather and with better visibility.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimated Coefficients</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schedule Factor</td>
<td>-0.064</td>
<td>0.004</td>
</tr>
<tr>
<td>Visibility</td>
<td>0.169</td>
<td>0</td>
</tr>
<tr>
<td>Weather</td>
<td>0.074</td>
<td>0.001</td>
</tr>
<tr>
<td>Vehicle Type</td>
<td>-0.332</td>
<td>0</td>
</tr>
<tr>
<td>Vehicle Speed</td>
<td>0.678</td>
<td>0</td>
</tr>
<tr>
<td>Train Speed</td>
<td>0.62</td>
<td>0</td>
</tr>
<tr>
<td>AADT</td>
<td>0.072</td>
<td>0.017</td>
</tr>
<tr>
<td>Area Type</td>
<td>-0.151</td>
<td>0</td>
</tr>
<tr>
<td>Pavement</td>
<td>0.174</td>
<td>0</td>
</tr>
<tr>
<td>Driver's Age</td>
<td>0.201</td>
<td>0</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.092</td>
<td>0</td>
</tr>
</tbody>
</table>

Number of Observations=15,880
Log likelihood =-1924
Pseudo R-Square=0.046
Sig.=0.000

TABLE 2 Ordered Probit Model Estimation Results

Highway users’ speed describes the driver’s estimated speed when the accident occurred. In this research this speed variable is classified into two levels: highway driver’s speed more than 50 mph and speed less than 50 mph which is the reference category. The research found speed more than 50 mph was significant with a positive coefficient of 0.678. The positive coefficient indicates an increased likelihood of higher severities at highway-rail crossing injuries for accidents involving vehicular speeds of more than 50 mph when compared to crossing vehicles with speeds less than 50 mph. Zhang et al. (24) found that the increase of speed limit on freeway will increase the injury severity of the crash. The Annual Average Daily Traffic (AADT) is categorized into two levels: “less than 10,000” and “AADT greater 10,000”. In addition, “AADT less than 10,000” is adopted as the base category. From Table 2, “AADT more than 10,000” is found to be significant with a positive coefficient 0.072. The positive coefficient value for “AADT more than 10,000” indicates the increased likelihood of severe highway-rail crossing injuries on high volume roads.
Railway information here is represented by train speed which describes the estimated train speed when the highway-rail crossing accident occurred. In this research this speed variable is classified into two levels: train speed more than 50 mph and speed less than 50 mph which is the reference category. The research found that speed “more than 50 mph” was significant with a positive coefficient of 0.62. The positive coefficient indicates an increased likelihood of higher severities of highway-rail crossing injuries if the train speed is “more than 50 mph” when compared to train speed “less than 50 mph”. A higher train speed means less reaction time for motor vehicle drivers given a highway-rail accident happened and thus increases the probability of higher injury severities at highway-rail crossings. In addition, McCollister et al. (12) found that increasing train speed will increase injury level which is intuitive.

Vehicle type is classified into two groups: “Truck and Truck-Trailer”, and “Auto and other” (other including van, bus, school bus, motorcycle, pedestrian.). “Auto and other” is chosen as the base category. This research found “Truck and Truck-Trailer” is significant with a negative coefficient of (-0.332). The negative coefficient value implies an decreased likelihood of driver injury severity at highway-rail crossing for “Truck and Truck-Trailer” vehicle drivers when compared to “Auto and other” drivers. McCollister et al. (12)”s study found that trucks are mandatory to stop at a highway-rail grade crossing intersections and truck drivers are used to be trained, professional and experienced drivers.

“Area” in this study includes two types: “open space” and “other areas” where “other areas” refer to industrial, commercial, residential and institutional areas. “Open space” is chosen as the reference category. The research found “other area” to be significant with a negative coefficient of -0.151. The negative coefficient indicates a decreased likelihood of higher severities of highway-rail crossing injuries if an accident happens in an area other than open space when compared to open area. This result may be due to driver’s lack of alertness and attention while driving in “open space” which may have low traffic volumes. Shankar et al. (21) in his study on single-vehicle motorcycle accident found that riders’ inattention will increase the likelihood of disabling injury in open space area. Zhang et al. (24) found that accidents located in residential zones will decrease the probability of severe injuries.

Roadways can be paved with timber, asphalt, concrete, rubber, or metal. The roadway pavement in this study is classified as “not-paved” and “paved” which is the reference category. The research found that “not-paved” is significant with a positive coefficient value of 0.174. The positive coefficient value indicates an increased likelihood of higher severities for highway-rail grade crossing accidents if the roadway surface is not paved when compared to a roadway with a paved surface. This could be attributable to the friction level of the roadway. An unpaved road has a lower friction force and therefore needs much more time to stop. As a result, an unpaved roadway will increase the probability of higher severities at highway-rail crossings.

Among the driver’s information, age has a significant effect on injury severity levels. However, the relationship between driver’s age and injury severity differs by age group. Age in this study is classified into two categories: “less than 50” and “over 50”. This category is based on Abdel-Aty et al. (15) and Zhang et al. (24) who looked at injury severity for highway vehicle accidents. “Age less than 50” is defined as the reference category. The research found “over 50” to be significant with positive coefficient 0.201. The positive coefficient value implies an increased likelihood of higher severities for highway-rail crossing injuries for accidents involving older drivers. Furthermore, although older drivers may tend to drive at lower speeds and less likely to be in an accident, once in an accident they tend to have severe injuries by Shankar et al. (21) and Pai et al. (17).
Gender is an important factor influencing driver’s injury severity. Female is defined as the reference category. The study found that the variable “male” is significant with a negative coefficient -0.092. The negative coefficient value implies a decreased likelihood of higher severities for highway-rail crossing injuries for accidents involving male drivers when compared to female drivers. Due to physiological differences, women are expected to sustain more severe injuries than men by Yan et al. (23) and Kockelman et al. (11).

**Marginal Effects Analysis**

The coefficients estimation in the previous section do not directly reflect the impact of contributing factors on each of the three types of injury levels: property damage only (PDO), injured, and killed. As a result, a marginal effects analysis of factors was conducted. The results in Table 3 illustrate the impact of contributing factors on each injury severity level. The coefficient values are classified as positive and negative. A positive marginal coefficient of a variable for a particular injury severity level means that the probability of the severity level will increase as the input variable increases by one unit. The marginal effects of ordered probit model in our study are determined using Limdep 9.0.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Property Damage Only</th>
<th>Injured</th>
<th>Killed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak Hour</td>
<td>-0.0068</td>
<td>0.0041</td>
<td>0.0027</td>
</tr>
<tr>
<td>Visibility</td>
<td>0.0785</td>
<td>-0.0484</td>
<td>-0.0301</td>
</tr>
<tr>
<td>Weather</td>
<td>-0.0406</td>
<td>0.0247</td>
<td>0.0159</td>
</tr>
<tr>
<td>Driver's Age</td>
<td>-0.0572</td>
<td>0.0335</td>
<td>0.0237</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.0002</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>Open Space</td>
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<td>0.0085</td>
<td>0.0058</td>
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<td>Pavement</td>
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<td>0.0723</td>
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<td>Vehicle Type</td>
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<td>-0.0514</td>
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<td>Vehicle Speed</td>
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<td>0.1517</td>
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<td>Train Speed</td>
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<td>0.1103</td>
<td>0.1131</td>
</tr>
<tr>
<td>AADT</td>
<td>-0.034</td>
<td>0.0208</td>
<td>0.0131</td>
</tr>
</tbody>
</table>

**TABLE 3 Marginal Effects of Ordered Probit Model**

From Table 3, the collision occurred during the “Peak hour” will increase the probability of driver being killed by 0.27% and driver injury portion by 0.41% compared with “no-peak” collision. Pai et al. (17) found that the risk of a severe injury and fatality is higher during the peak period compared with off peak period for motor vehicle drivers in highway collisions.

The variable “bad weather” condition includes cloudy, rain, fog, sleet, and snow. The bad weather condition will decrease the probability of “property damage only accidents” by 4.06% compared with clear day condition; on the contrary, it will increase the probability of injured level accidents by 2.47% and killed level accidents by 1.59%. The visibility level “dark” was found to decrease the probability of a driver being killed by 3.01% and decrease the probability of the driver being injured by 4.84% compared with clear condition, whereas it will increase “property damage only level” accidents by 7.85%.
Drivers older than 50 years are more likely to be “injured” or “killed” in a highway-grade crossing accident when compared to drivers that are younger than 50 years. From Table 3, drivers older than 50 years will increase the probability of being injured by 3.35 percent and killed by 2.37 percent compared with drivers younger than 50 years. The increase of the probability of being injured and killed can be explained by studies which have shown that crash severity increases with age. Abdel-Aty et al. (15) found that older drivers have a higher probability of more severe injuries especially for drivers above 80 years old.

An accident occurring in an “Open space” area will increase the probability of the driver being killed by 0.58% and the driver being injured by 0.85% compared with an accident occurring in residential, commercial, and industrial areas. Similarly, Abdel-Aty et al. (15) found that rural area had a positive influence to increase the probability of driver injury severity levels. In addition, an accident occurring on at a crossing with “Paved road” will decrease the probability of the driver being killed by 7.23% and the driver being injured by 8.22% compared with “unpaved” road.

Highway vehicle drivers’ with a crossing speed of more than 50 mph is found to increase the probability of a driver being killed by 15.17% and the driver being injured by 11.5% compared with vehicle drivers with speeds less than 50 mph.”. Abdel-Aty et al. (15) found that speed increased the probability of severe injuries. For vehicle information, “Truck and Truck-trailer” drivers will decrease the probability of driver killed level accidents by 5.14% and driver injured level accidents by 9.02% compared with other vehicle drivers. This can be explained by the fact that truck drivers are professional and experienced drivers by McCollister et al. (12). In addition, truck drivers are required to stop at a highway-grade crossing regardless of the state of the crossing device.

Train speeds greater than 50 mph was found to increase the probability of a driver being killed at highway-grade crossing accidents by 11.31% and injured by 11.03% compared with a lower train speed. Drivers need to have minimal reaction time to stop once an oncoming train is detected. If the train is coming too fast to cross the highway-grade crossing, highway vehicle drivers will not have enough time to stop and it will significantly increase the likelihood of “killed level” accidents and “injured level” accidents. McCollister et al. (12) found that increasing train speed had more effect on injuries and even greater effect on fatalities given that a highway-grade crossing accident occurred.

CONCLUSIONS
An ordered probit model is introduced in this study to analyze the factors influencing driver’s injury severity at highway-grade crossings. The model was developed using accidents from 2002-2011 locations all over the United States. As a result, the research uses a dataset which is the latest and comprehensive data file. Analysis of the ordered probit model in our study reveals crucial factors influencing highway driver’s injury severity, and it will also provide potential strategies to reduce driver injury severity at highway-grade crossings. Based on the data estimation and marginal analysis results, it was found that the factors significantly impacting the probability of driver injury severity include peak hour, weather, visibility, vehicle type, vehicle speed, AADT, train speed, driver’s age, gender, area type and highway pavement. A marginal analysis was provided to quantitatively explain the marginal effects of each independent variable on each injury level.

The research found that female drivers are more likely to have severe highway-grade crossing injuries compared to male drivers. Older drivers are more susceptible than younger...
drivers to cause severe highway-rail crossing accidents. Severe highway-rail crossing injury accidents are most likely be influenced by bad weather road condition, such as wet, icy or snowy road surface, and by visibility, such as dark conditions. In addition, lower train and roadway speed limits will significantly reduce driver injury severity.

Although previous researchers have focused on analyzing the frequency of crashes at highway-rail grade-crossings, few studies have been conducted on driver’s injury severity level. In addition, previous driver injury level studies at highway-rail grade crossing did not account for the ordered nature of injury levels by Miranda-Moreno et al. (13); Hu et al. (10); McCollister et al. (12). This research attempted to identify contributing factors which influenced the driver’s injury severity at highway-rail grade crossings. This study provides differences in methodology and dataset and results in a contribution to this field of safety at highway-rail crossings. The findings are beneficial to transportation engineers to improve safety performance at highway-rail grade crossings.

Further studies should be performed to address the limitations of this study. The assumption of this study suggests that the input variables are independent among each other. The potential correlations between each variable are not considered. Highway driver’s information is found to be significant variable to influence driver injury severity at highway-rail grade crossings. As a result, more driver behavior information, such as alcohol involvement and education status, should also be collected to provide more drivers’ information.
REFERENCES:


