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2009

Study on crash characteristics and injury severity at roadway work zones

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Study On Crash Characteristics And Injury Severity At Roadway Work Zones

by

Qing Wang

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering Department of Civil & Environmental Engineering College of Engineering University of South Florida

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> > Date of Approval: March 26, 2009

Keywords: ordered probit regression, descriptive statistics, age groups, traffic safety, marginal effects

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ACKNOWLEDGMENTS

It is with great pride that I thank the brilliant minds affiliated with the Department of Civil and Environment Engineering at the University of South Florida. I would like to give special thanks to my major professor, Dr. Jian John Lu, for the guidance he has provided. In addition, I would like to thank committee members Dr. Abdul Pinjari, Dr. Yu Zhang, and Dr. Zhenyu Wang. This thesis would not have been possible without your contributions.

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Study on Crash Characteristics and Injury Severity at Roadway Work Zones

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ABSTRACT

In USA, despite recent efforts to improve work zone safety, the number of crashes and fatalities at work zones has increased continuously over several past years. For addressing the existing safety problems, a clear understanding of the characteristics of work zone crashes is necessary. This thesis summarized a research study focusing on work zone traffic crash analysis to investigate the characteristics of work zone crashes and to identify the factors contributing to injury severity at work zones. These factors included roadway design, environmental conditions, traffic conditions and vehicle/driver features. Especially, special population groups, which divided into older, middle Age, and young, were inspected. This study was based on history crash data from the Florida State, which were extracted from the Florida CAR (Crash Analysis Reporting) system. Descriptive statistics method was used to find the characteristics of crashes at work zones. After then, an injury severity predict model, using the ordered probit regression technology, was developed to investigate the impacts of various factors on different the injury severity at work zones. From the model, it can be concluded that some factors,

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including the road section with curve, alcohol/drugs involved, a high speed, angle crash and too young or old drivers are more likely to increase the probability of angle crashes. Based on the magnitudes of the variable coefficients, the factor of maximum posted speed have a great impact to injury severity, which shows restriction to driving speed is principle countermeasure for improving work zone safety.

CHAPTER ONE

INTRODUCTION

1.1 Background

In Highway Capacity Manual 2002, the definition of work zone is a segment of highway in which maintenance and construction operations impinge on the number of lanes available to traffic or affect the operational characteristics of traffic flowing through the segment. It should be typically marked by signs, channelizing devices, barriers, pavement marking, and/or work vehicles. It extends from the first warming sign or high-intensity rotating, flashing, oscillating, or strobe lights on a vehicle to the "End Road Work" sigh or the last temporary traffic control device. The Manual on Uniform Traffic Control Devices lists five distinct areas within a work zone. Each of these has a specific purpose and may vary in size and location depending on the specifics of each work zone. The five areas are: advance warning area, transition area, activity area, buffer space, and termination area (Figure 1.1).

The advance warning area is the section of highway where road users are informed about the upcoming work zone or incident area. The transition area is that section of highway where road users are redirected out of their normal path. Transition areas usually involve strategic use of tapers, which because of their importance are discussed

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Figure 1.1 Component Parts of a Work Zone

separately in detail. The activity area is the section of the highway where the work activity takes place. It is comprised of the work space, the traffic space, and the buffer space. The work space is that portion of the highway closed to road users and set aside for workers, equipment, and material, and a shadow vehicle if one is used upstream. Work spaces are usually delineated for road users by channelizing devices or, to exclude vehicles and pedestrians, by temporary barriers. Typically, the buffer space is formed as a traffic island and defined by channelizing devices. When a shadow vehicle, arrow panel, or changeable message sign is placed in a closed lane in advance of a work space, only the area upstream of the vehicle, arrow panel, or changeable message sign constitutes the buffer space. The termination is the end area of work zone.

Work zone safety has always been a high priority issue in highway systems but remains unsatisfactory in USA. Based on the statistics from FHWA (Federal Highway Administration), in 2007, there were 835 work zone fatalities, which represent 2.0% of all roadway fatalities for the year. Over four out of every five-work zone fatalities were motorists. In addition, there are over 40,000 injuries at work zones. The total cost of highway work zone injuries calculates to \$9.25 billion per year. The highway work zone fatalities per billion dollars spent, are at list 4 times more than in total construction (Maze et al., 2000). Estimating between 1995 and 1997, the direct costs of highway construction zone accidents were as high as \$6.2 billion per year, and the average cost is \$3687 per accident (Mohan and Gautam, 2002)

To improve work zone safety, four fields need to be approached contemporaneously: engineering, education, enforcement, and coordination with public agencies.

Engineering: This focuses on standardization and evaluation. The standardization part is for traffic control and safety devices in work zone areas. The MUTCD (Manual on Uniform Traffic Control Devices) is the national safety standards to control traffic through work zones, and the NCHRP350 (National Cooperative Highway Research Program Report 350 "Recommended Procedures for the Safety Performance Evaluation of Highway Features") contains the federal standards and guidelines for all work zone safety devices. The national guidelines regarding planning and implementing work zones is keeping update to address the changing times of more traffic more congestion, greater safety issues, and more work zones.

Education: Public awareness is improved through a variety of activities like clearinghouse website [\(www.workzonesafety.org\)](http://wwwcf.fhwa.dot.gov/exit.cfm?link=http://www.workzonesafety.org/); training courses for federal, state, local and tribal highway engineers; conferences, CDs; guidebooks; brochures (for the general public and highway practitioners); bilingual safety public outreach materials; and press events such as National Work Zone Awareness Week.

Enforcement: Engineers in federal highway work closely with state highway to identify appropriate engineering safety countermeasures for high-risk locations new roads. They also work with the enforcement community such as the IACP (International Association of Chiefs of Police). Speed enforcement is a top safety concern in work

zones since it has critical relationship with crash severity. In Maryland, Michigan and Virginia, VSL (Variable speed Limits) demonstration projects which determine appropriate speeds for work zones and change them when conditions change were to analyze variations on speed and accompany driver behavior.

Association: Working with emergency medical services, police and fire organizations can ensure that public safety is maintained at high levels and access for emergency vehicles is possible during work zone operations. AASHTO (American Association of State Highway and Transportation Officials), ATSSA (American Traffic Safety Services Association) and FHWA found the National Work Zone Awareness Week in April every year to bring national attention to motorist and worker safety and mobility issues in work zones. Beside this, lots of other publications like Basic Traffic Control for Utility Operations manual and Strategic Highway Safety Plan are the productions by more than one partner or sponsor.

Researching the characteristics of crashes is the very first step of learning the deficiencies of work zone safety and countermeasures. In addition, studying the characteristic differences between each crash injury severity level may cause the discovery of factors influencing injury severity change, which could benefit the development of traffic controls for reducing the proportion of high-severity crashes in total crashes.

1.2 Research Objectives and Approaches

The main objectives of this study are to investigate the characteristics of accidents in work zones, to identify the factors contributing to injury severity levels, and to study how these factors influence injury levels. For more specifically, this study follows these steps:

(1) Review the previous researches in the field of work zone crash characteristics and injury severity models.

(2) Determine the most promising model for model development part by comparing various models in literature review part.

(3) Investigate the differences of characteristics such as crash severity, environmental conditions, crash types and contributing factors among three driver age groups.

(4) Develop a crash severity model for the identification of the most significant factors contributing to the injury severity levels.

1.3 Organization

This thesis consists of five chapters. Chapter 1 provides a brief introduction of the research, including the background of the research, research objective and approaches. Chapter 2 discusses the past studies in both work zone crash characteristics and crash injury severity models, and chooses the most appropriate model to develop the work zone injury severity model for this study. Chapter 3 compares the descriptive characteristics of

work zone crashes in three age groups, including the crash severity, environmental conditions and some other contributing factors. A crash injury severity model is produced and interpreted; the factors that influence crash severity levels are found are given in chapter 4. Finally, chapter 6 provides a summary and the conclusion of this research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Previous Studies on Work Zone Crashes

Many studies have been performed on accident experience within work area in the United States. Most of them focus on the crash characteristic in diverse work zone types, crash severity levels, and different locations within work zone.

Ullman et al. (2005) presented an analysis of the safety effects of night work activity upon crashes at two types of construction projects in Texas. The first project type involved both day and night work, whereas the other project type involved pavement resurfacing activities performed only at night. They found that crashes increased more significantly during periods of work activity than during periods when the work zone was inactive. Overall, the increase during work activity was somewhat higher at night than during the day. Researchers also found that crashes increased more at night than during the day at the hybrid projects even when the work zone was inactive, presumably reflecting a disproportionate influence of the temporary geometrics and traffic control upon nighttime travel at these sites.

77 fatal work zone crash sites throughout Texas from Feb. 2003 to Apr. 2004 were analyzed by Schrick (2004). Based on these investigations, researchers concluded that

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only 8 percent of the investigated crashes had a direct influence from the work zone, whereas 39 percent of the investigated crashes had an indirect influence from the work zone. Researchers also concluded that 45 percent of the investigated crashes appeared to have no influence from the work zone (included in this subset are the 16 percent of the investigated crashes which occurred in work zones that were work zones in name only, such as work zones that consisted only of project limit signing).

The characteristics of highway work zone collisions and their detailed locations within work zones were studied by Garber and Zhao (2002) to enhance the selection of effective countermeasures. The objective was to determine the distribution and characteristics of crashes in specific areas within a work zone and to compare selected characteristics of work zone crashes with those of non-work zone crashes. In their study, the different locations in the work zone were referred to as the advance warning area, transition area (taper), longitudinal buffer area, activity area, and termination area. Based on the crash percentages regarding location, severity, and collision type, the researchers concluded several major findings. First, the activity area had the highest number of crashes and the highest number of fatal crashes while the termination area was the safest area in terms of numbers of crashes. Second, property-damage-only (PDO) crashes were the predominant severity type, followed by the injury crashes. Third, rear-end crashes were predominant for all areas and all road types except for the termination area, where all crashes were angle crashes. Fourth, as traffic moved from the transition area to the

work area, the proportions of rear-end and same-direction sideswipe crashes decreased and the proportions of fixed-object, off-road, and angle crashes increased, although rear-end crashes were still predominant. Last, most nighttime work zone crashes were in the activity area and the severities of nighttime and daytime work zone crashes were not significantly different.

In 2000, Daniel et al. performed a study which was expanded further to examine the difference between fatal crash activity within work zones compared with fatal crashes in non-work-zone locations. Using data from three work zone locations in Georgia, fatal crash activity within work zones also was compared with nonfatal crashes within work zones. Finally, fatal crash activity was examined to determine the influence of the work zone activity on the frequency of fatal crashes. The overall findings of the study indicate that the work zone influences the manner of collision, light conditions, truck involvement, and roadway functional classification under which fatal crashes occur. The study also indicates that fatal crashes in work zones are more likely to involve another vehicle than non-work-zone fatal crashes, and fatal crashes in work zones are less influenced by horizontal and vertical alignment than are non-work-zone crashes.

Khattak et al. (2002) created a unique dataset of California freeway work zones that included crash data (crash frequency and injury severity), road inventory data (average daily traffic and urban/rural character), and work zone related data (duration, length, and location). Crash rates and crash frequencies were investigated in the pre-work zone and

during-work zone periods. For the freeway work zones investigated in this study, the total crash rate in the during-work zone period was 21.5% higher (0.79 crashes per million vehicle km) than the pre-work zone period (0.65 crashes per million vehicle km). Compared to the pre-work zone period, the increase in non-injury and injury crash rates in the during-work zone period was 23.8% and 17.3%, respectively. Next, crash frequencies were investigated using negative binomial models, which showed that frequencies increased with increasing work zone duration, length, and average daily traffic.

Wang et al. (1996) discussed the primary questions that safety researches are attempting to answer. The results were presented of an investigation to (a) determined what is known about the magnitude of highway work zone crashes, (b) examined characteristics of highway work zone crashes using the Highway Safety Information System, (c) investigated how work zone accidents are reported on police accident report forms and within state accident report systems, (d) identified critical voids in the knowledge of the relative safety of work zones, and (e) examined possible ways to address unfulfilled information needs related to work zone safety.

2.2 Previous Studies on Crash Severity Model

Researchers have employed many statistical techniques to analyze crash severity level. Among these techniques were log-linear, logit, and probit models.

2.2.1 Log-linear Model

Using 1994 and 1995 crash data from Florida, Abdel-Aty et al. (1998) used log-linear technique to examine relationships between driver age and crash characteristics. The three injury severities in their study were no injury, injury and fatality, and their results suggest that injury severity is positively associated with age; they also concluded that middle-age drivers are more likely to be involved in some crashes, but older drivers are more likely to be involved in fatal crashes. Kim et al. (1995) used log-linear models to predict automobile crash and injury severity. The results suggested that alcohol or drug use and lack of seat belt use increase the odds of more severe crashes and injuries.

2.2.2 Logit Model

Logistic regression models were developed by Donnell and Mason (2004) using both an ordinal and a nominal response. The results indicateed that modeling crash severity as an ordinal response provided appropriate results for cross-median crashes, whereas a nominal response was more appropriate for median barrier crashes. Explanatory variables such as pavement surface conditions, use of drugs or alcohol, presence of an interchange entrance ramp, horizontal alignment, crash type, and average daily traffic volumes affect crash severity. The analysis results might be used by practitioners to understand the trade-off between geometric design decisions and median-related crash severity. Approximately 0.7% median barrier crashes on the

Interstate system resulted in a fatality, whereas 43% were property-damage-only crashes and about 56% were injury crashes. More than 17% of cross-median collisions were fatal, and 67% involved injury.

Modeling severity as a discrete outcome involves estimating the probability that a vehicular crash has a certain severity by determining the likelihood of outcomes given that a crash has occurred. Lee and Chang (2002) estimated the severity of run-off-road crashes in the state of Washington, again by using the nested logit model. Temporal, environmental, driver, roadway, and roadside characteristics were used to estimate property damage and possible injury probabilities for rural run-off-road crashes conditioned on no evident injury. The findings indicated that wet pavement surfaces resulted in possible injury, drivers younger than 25 were more likely to be involved in injury crashes, alcohol-impaired drivers were more likely to be involved in injury crashes, and crashes in the presence of a horizontal curve were more likely to involve an injury.

Dissanayake and Lu (2002) used binary logistic regression model takes the following form. Factors that prove most influential in predicting severity in young driver crashes included influence of alcohol or drugs, ejection in the crash, point of impact, crash location, existence of horizontal curve or vertical grades at the crash site, speed of the vehicle, and restraint device usage.

Krull, Khattak, and Council (2000) used logit models to analyze driver injury severity involved in a single-vehicle crash. Three-year crash data from Michigan and

Illinois were analyzed to explore the effect of rollover, while controlling for roadway, vehicle, and driver factors. Results showed that driver injury severity increases with: (a) failure to use a seatbelt, (b) passenger cars as opposed to pick-up trucks, (c) alcohol use, (d) daylight, (e) rural roads as opposed to urban, (f) posted speed limit, and (g) dry pavement as opposed to slippery pavement.

Chang and Mannering (1999) estimated a nested logit model to study the occupancy crash injury severity relationship. Crash data of principle arterials, state highways, and interstates in Seattle, Washington, during 1994 were used in the analysis. The dependent variable was the crash severity, which represents the most severe level of injury sustained by any vehicle occupant involved in the crash. The occupancy can be significant because vehicles with large occupancies have an increased likelihood of having someone seriously injured. Separate models were estimated for non-truck-involved crashes and for non-truck-involved crashes. Results showed that increased severity was more likely for truck-involved crashes, high speed limits, crashes occurring when a vehicle is making a right or left turn, and rear-end types of collisions.

Shankar, Mannering, and Barfield (1996) estimated a nested logit model to analyze crash severity of single-vehicle crashes on rural freeways. All possible nesting structures (which examine possible correlation among the choices) were considered and statistically tested by the likelihood ratio test. The authors found that a nested-logit model, which

treated property damage only (no injury) and possible shared characteristics of injury crashes, fits the data best.

Shankar and Mannering (1996) used a multinomial logit specification for estimating motorcycle rider crash severity likelihood conditioned on the occurrence of a crash. Five levels of severity are considered: property damage only, possible injury, evident injury, severe injury, and fatality. Crash data were 5-year statewide data on single-vehicle motorcycle crash from the state of Washington. Results showed that the multinomial logit formulation is a promising approach to evaluate the determinants of motorcycle crash severity.

Nassar, Saccomanno, and Shortreed (1994) estimated a nested logit model to predict crash severity. Three separate models were calibrated for three crash situations: single-vehicle, two-vehicle, and multi-vehicle crashes. Factors that affect the level of damage experienced by individuals involved in traffic crashes include a crash dynamic term, seating position, seat belt use, vehicle condition, vehicle mass, driver condition, and driver action. Road surface condition was insignificant in the models. Bad weather conditions may prompt drivers to slow down and keep a safe distance from other vehicles.

2.2.3 Probit Model

Abdel-Aty and Keller (2005) produced ordered probit models for crash severity level and used the tree-based regression to explore the factors which affect injury level. The results of this research showed that when attempting to forecast the number of expected crashes of different severity levels, it is imperative that models are developed for each level of collision instead of aggregating crash types to predict the overall severity level. While the ordered probit model approach had been adopted, as did many previous researchers, using the tree-based regression for each severity level improved our understanding of the specific factors and their importance for each severity level. Furthermore, the results showed that crashes reported on short-forms are important and should therefore be retained and included in crash databases. Ignoring this data could lead to biasing the results by under reporting crashes of certain severity or type that could be related to specific explanatory factors. Other crash types or severities might appear to have higher percentages, and therefore, their effect could be artificially exaggerated.

Khattak and Targa (2004), Khattak et al. (2002, 2003) used ordered probit models to predict the injury level for crashes occurring at construction zones and involving trucks, to predict injury severity for single-vehicle truck rollovers, and to determine vehicle, roadway, driver, crash, and environmental characteristics that influence the severity level of older drivers involved in crashes, respectively.

Abdel-Aty (2003) applied the ordered probit models to predict crash injury severity on roadway sections, signalized intersections and toll plazas. Models explained a driver's violation was significant in the case of signalized intersections. Alcohol, lighting conditions, and the existence of a horizontal curve affected the likelihood of injuries in the roadway sections' model. A variable specific to toll plazas, vehicles equipped with Electronic Toll Collection (ETC), had a positive effect on the probability of higher injury severity at toll plazas. Other variables that entered into some of the models were weather condition, area type, and some interaction factors. This study illustrates the similarities and the differences in the factors that affect injury severity between different locations.

Kockelman and Kweon (2002) described the use of ordered probit models to examine the risk of different injury levels sustained under all crash types, two-vehicle crashes, and single-vehicle crashes. The results suggested that pickups and sport utility vehicles are less safe than passenger cars under single-vehicle crash conditions. In two-vehicle crashes, however, these vehicle types were associated with less severe injuries for their drivers – and more severe injuries for occupants of their collision partners. Other conclusions also were presented; for example, the results indicated that males and younger drivers in newer vehicles at lower speeds sustain less severe injuries.

Toshiyuki and Shankar (2002) used a bivariate ordered-response probit model to study driver and most severely injured passenger severity in collision with fixed objects in Washington State. Results showed that icy roadway surface and rain decrease the

probability of more severe driver injury. The type of fixed objects significantly affects driver's injury severity. Guardrails have different effects on driver's injury whether the collisions are with its face or with its leading end. Proper use of a restraint system significantly decreases the probability of more severe driver injury. Male and younger drivers have a lower probability of more severe injury, probably because of their physical strength. Also, driver's unconsciousness causes more severe driver injury.

Duncan, Khattak, and Council (1999) used ordered probit modeling to examine the occupant characteristics and roadway and environmental conditions that influence injury severity in rear-end crashes involving truck-passenger car collisions. Two models were developed, one with the basic variables and the other including interactions among the independent variables. Results revealed that an increased severity risk exists for higher speed crashes, those occurring at night, for women, when alcohol is involved, and for crashes when a passenger car rear-ends a truck at a large differential speed between the two vehicles.

Khattak (1999) applied the ordered probit model to examine the effect of information (accuracy of information conveyed by brake and turning lights) and other factors on rear-end crash propagation and the propensity of driver injury in such crashes. Results on injury severity showed that in a two-vehicle crash, the leading driver is more likely to be injured, whereas, in a three-vehicle crash, the driver in the middle is likely to

be more severely injured. Furthermore, as rear-end crashes propagate from two-vehicles to three-vehicles the last driver is relatively less severely injured.

Klop (1998) examined the impacts of physical and environmental factors on the severity of injury to bicyclists in North Carolina. Using the ordered probit model, the effect of a set of roadway, environmental, and crash variables on injury severity was explored. Separate models were estimated for rural and urban locations. Results indicated that straight grades, curved grades, darkness, and fog significantly increase injury severity.

Renski, Khattak, and Council (1998) estimated ordered probit models to explore the effects of policy variables on injury severity. Results showed that highway segments where speed limits were raised by 10 mph resulted in a higher probability of increased severity than those raised by only 5 mph. No significant changes in injury severity were found for the highway segments where speed limits were raised from 65 to 70 mph.

In assessing the probabilities of four levels of injury severity as a function of driver attributes, O'Donnell and Connor (1996) compared ordered logit and ordered probit specifications. Their results suggest that injury severity rises with speed, vehicle age, occupant age (squared), female gender, blood alcohol levels over 0.08 percent, non-use of a seatbelt, manner of collision (e.g., head-on crashes), and travel in a light-duty truck. And, according to their comparison of effects, seating position of crash victims was most relevant (e.g., the left-rear seat of the vehicle was found to be most dangerous) and

gender least relevant. Many of their results are echoed in the models presented here; the key distinction is that here collision partners and crash-type are examined and emphasized.

Hutchinson (1986) developed an ordered probit model to study occupants' injury severity when involved in traffic crashes. British crash data for 1962–1972 had been processed to give a cross-tabulation of the severity of injury to the driver and to the front seat passenger in four types of single-vehicle crashes (overturning and non-overturning, each in rural and urban areas). Results showed that passengers tend to be more seriously injured than drivers in nonoverturning, but that there is no difference in overturning crashes.

CHAPTER THREE

DESCRIPTIVE STATISTICS ANALYSIS

3.1 The Trend of Crashes

The trend of work zone crashes and fatal crashes are ascending continuously from 2002 to 2006 in Florida (see Figure 3.1). The average annual increase rate of work zone crashes is 18.8%, and the fatal crashes in 2006 are 64.4% more than one in 2002. This trend indicates that the work zone safety in Florida remained a serious concern.

Figure 3.1 Work Zone Crashes and Work Zone Fatal Crashes in Florida

3.2 Distribution of Crashes by Drivers' Age

Figure 3.2 shows the age distribution of the at-fault drivers for work zone and non-work zone crashes. The drivers are divided into three age groups: Young Age (less than 25), Middle Age $(25 - 64)$ and Elderly Age (greater than 65). In work zone area, the middle age drivers cause the highest proportion (67%) of crashes, while the elderly drivers are only responsible for 9% of the crashes. The driver group having the second highest crash rate (24%) is the young age drivers. Compared to work zone crashes, middle age drivers in non-work zone area have a lower possibility of occurring crashes (63%).

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3.3 Distribution of Crashes by Crash Severity

The distribution of work zone crashes by crash severity is shown in Figure 3.3, which indicates that the middle age drivers involved the highest percentage in the no injury crashes which is 49%, and always has the lowest percentage in other severity levels. While in the more severe level crashes, elderly drivers contribute more than the other two age groups (Incapacitating Injury: Old Drivers 9% and Fatal Injury: Old Drivers 2%).

Figure 3.3 Distribution of Work Zone Crashes by Crash Severity

3.4 Distribution of Crashes by Climatic Environmental Conditions

Climatic Environmental conditions include lighting conditions, weather conditions, and road surface conditions. Figure 3.4 summarizes the distribution of crashes by lighting conditions. Most crashes occur when lighting condition is good. Elderly drivers is most likely to having crashes under good lighting condition (daylight), and only has 18% crashes under non-daylight condition including dawn, dusk and dark conditions. In contrast, the difference of crash rate between these two lighting conditions in young drivers is not remarkable.

□ Young ■ Middle ■ Old

Figure 3.4 Distribution of Work Zone Crashes by Lighting Conditions

The results of analysis of the distribution of work zone crashes by weather and road surface conditions are shown in Figures 3.5 and 3.6 respectively. The results indicate that in all three age groups only a small proportion of work zone crashes occur in bad weather or bad road surface conditions. In contrast to the common sense, the adverse weather and road conditions do not have significant influence on the work zone fatal crashes.

Figure 3.5 Distribution of Work Zone Crashes by Weather Conditions

Figure 3.6 Distribution of Work Zone Crashes by Road Surface Conditions

3.5 Distribution of Crashes by Crash Types

As illustrated in Figure 3.7, the top three work zone crash types in all age groups are the same. There are rear-end, angle and sideswipe which are defined as the principle crash types in this study. In young and middle age groups, the percentage of rear-end crashes is obviously higher than angle and sideswipe crashes. Elderly age group shows higher rate in angle crashes than others. Compared work zone and non-work zone crash types in Figure 3.8, read-end and sideswipe crashes are more likely to be occurred in work zone area.

□ Young ■ Middle ■ Old

Figure 3.7 Distribution of Work Zone Crashes by Crash Types

Figure 3.8 Distribution of Work Zone and Non-work Zone Crashes by Crash Types

3.6 Distribution of Crashes by Contributing Factors

Figure 3.9 represents the distribution of contributing factors by all drivers and each age group. Among all drivers, careless driving, the most predominant contributing factor, is responsible for 43% of total crashes. Another predominant factor is failed to yield right of way (11%) followed by no improper driving action (10%) and improper lane change (7%) respectively. In young and middle age group, the distributions are basically same as

which of all drivers, except that young drivers show slightly higher rate in careless driving (48%), and the second and third factors which are not variant too much in rate. But in elderly age group, the rate of first factor is just 34% and second one is more than 10% higher than other two age groups.

Figure 3.9 Distribution of Work Zone Crashes by Contributing Factors

Figure 3.10 to 3.12 express the distribution of predominant contributing factors over the principal crash types. The most predominant contributing factor for rear-end crashes is careless driving (average 74% in all three age groups). A difference between elderly age group and the other two age groups is that improper lane change is not a predominant

contributing factor for older age drivers but it is for young age drivers and middle age drivers.

Figure 3.10 Distribution of Work Zone Rear-end Crashes by Contributing Factors

Failed to yield right of way is the most predominant contributing factors for angle crashes. In elderly age group, the rate of this crash type is significantly higher than young and middle age groups; otherwise the rate of careless driving is less than others.

For sideswipe crashes, the improper lane change is the most frequent contributing factor in middle (36%) and elderly (40%) age group, and second most one is careless driving (19% for both groups). However, for young drivers, the top two factors have no much difference (27% for improper lane change and 30% for careless driving).

Figure 3.11 Distribution of Work Zone Angle Crashes by Contributing Factors

Figure 3.12 Distribution of Work Zone Sideswipe Crashes by Contributing Factors

3.7 Predominant Factors for Other Variables

The distributions of alcohol/drug involved and heavy vehicle (heavy truck and truck tractor) involved are given in Figure 3.13, 3.14 and 3.15. Old drivers are seldom influenced by alcohol/drug (only 1% involved), and most work zone crashes for young age group is not included by heavy vehicle. But heavy vehicle is more easily related to work zone crashes (14%) than non-work zone crashes (7%).

□ Young ■ Middle ■ Old

Figure 3.13 Distribution of Work Zone Crashes by Alcohol/Drug Involved

Figure 3.14 Distribution of Work Zone Crashes by Heavy Vehicle Involved

Figure 3.15 Distribution of Work Zone and Non-work Zone Crashes by Heavy Vehicle Involved

CHAPTER FOUR

CRASH SEVERITY MODEL

4.1 Methodology

As stated in previous papers, In contrast to the multinomial models which neglect the data's ordinarily and require more parameters estimated and nested logit models that produce better results but have complexity in identifying the nesting structure, the ordered probit models with a relatively simple approach recognize the indexed nature of various response variables. They are recommended to analyze the crash severity levels.

4.1.1 Crash Severity Models

The crash severity model in this study was developed to investigate the factors that affect crash severity in work zone area. The dependent variable in the model is injury severity level, and the independent variables are the factors which have significant influence on the crash severity. The crash injury severity is a typical ordinal variable which could be categorized at five levels from the least severe level to the most severe level (shown in Table 4.1).

| Level | Definition | Description |
|----------------|------------------------------|---|
| | No Injury | there is no reason to believe any person received bodily harm from the crash |
| $\overline{2}$ | Possible Injury | No visible signs of injury but complaint of pain or momentary unconsciousness |
| 3 | Non-incapacitating Injury | Visible injuries from the such as bruises, abrasions, limping, etc. |
| 4 | Incapacitating Injury | Any visible signs of injury from the crash and person(s) had to be carried from the scene. |
| | Fatal Injury | an injury sustained in a motor vehicle crash that results in death within 90 days |

Table 4.1 Definition and Description of Crash Severity Level

4.1.2 Ordered Probit Regression

The ordered probit model is as followed:

$$
y_i^* = \alpha + x_i \beta + \varepsilon_i \tag{4.1}
$$

where y_i^* is the latent and continuous measure of crash injury severity; *i* is the number of crashes faced by this severity level; x_i is a vector of parameters to be estimated; ε_i is a random error term which assumed to follow a normal distribution with mean 0 and variance 1. The pdf (Probability Density Function) is

$$
\phi(\varepsilon) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\varepsilon^2}{2}\right) \tag{4.2}
$$

and the cdf (Cumulative distribution Function) is

$$
\Phi(\varepsilon) = \int_{-\infty}^{\varepsilon} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\varepsilon^2}{2}\right) dt \tag{4.3}
$$

The observed and coded discrete crash injury severity variable *y* is determined from the model as follows:

$$
y_{i} = \begin{cases} 1 & \text{If } -\infty \leq y_{i}^{*} < \tau_{1} \\ 2 & \text{If } \tau_{1} \leq y_{i}^{*} < \tau_{2} \\ 3 & \text{If } \tau_{2} \leq y_{i}^{*} < \tau_{3} \\ \vdots & \vdots & \vdots \\ n-1 & \text{If } \tau_{n-2} \leq y_{i}^{*} < \tau_{n-1} \\ n & \text{If } \tau_{n-1} \leq y_{i}^{*} < \infty \end{cases}
$$
\n
$$
(4.4)
$$

This mapping from the latent variable to the observed crash injury severity class is illustrated in Figure 4.1.

Consider Figure 4.2 which shows the distribution of y^* for four values of *x*. The errors are distributed normally around the regression line $E(y^*|x) = \alpha + \beta x$. The Probability of outcome *m* corresponds to the area of the error distribution between the cutpoints τ_{m-1} and τ_m . This area is computed as follows.

First consider the formula for the probability that $y = 1$. We observe $y = 1$ when y^* falls between $\tau_0 = -\infty$ and τ_1 . This implies that

$$
\Pr(y_i = 1 | x_i) = \Pr(\tau_0 \le y_i^* < \tau_1 | x_i) \tag{4.5}
$$

Substituting $y_i^* = \alpha + x_i \beta + \varepsilon_i$,

$$
Pr(y_i = 1 | x_i) = Pr(\tau_0 \le \alpha + x_i \beta + \varepsilon < \tau_1 | x_i) \tag{4.6}
$$

Then, subtracting $x\beta$ within the inequality,

$$
\Pr(y_i = 1 | x_i) = \Pr(\tau_0 - \alpha - x_i \beta \le \varepsilon < \tau_1 - \alpha - x_i \beta | x_i) \tag{4.7}
$$

The probability that a random variable is between two values is the difference between the cdf evaluated at these values. Therefore,

$$
Pr(y_i = 1 | x_i) = Pr(\varepsilon < \tau_1 - \alpha - x_i \beta | x_i) - Pr(\varepsilon < \tau_0 - \alpha - x_i \beta | x_i)
$$

=
$$
F(\tau_1 - \alpha - x_i \beta) - F(\tau_0 - \alpha - x_i \beta)
$$
 (4.8)

These steps can be generalized to compute the probability of any observed outcome $y = m$ given *x*:

$$
Pr(y_i = m | x_i) = F(\tau_m - \alpha - x_i \beta) - F(\tau_{m-1} - \alpha - x_i \beta)
$$
\n(4.9)

When computing $Pr(y = 1|x)$, the second term on the right-hand side drops out since $F(\tau_0 - x\beta) = F(-\infty - x\beta) = 0$; when computing $Pr(y = J|x)$, the first term equal 1 since

 $F(\tau_J - x\beta) = F(\infty - x\beta) = 1$. Thus, for a model with four observed outcomes, such as

shown in Figure 4.2, the formulas for the ordered probit model are

$$
Pr(y_i = 1|x_i) = \Phi(\tau_1 - \alpha - \beta x_i)
$$

\n
$$
Pr(y_i = 2|x_i) = \Phi(\tau_2 - \alpha - \beta x_i) - \Phi(\tau_1 - \alpha - \beta x_i)
$$

\n
$$
Pr(y_i = 3|x_i) = \Phi(\tau_3 - \alpha - \beta x_i) - \Phi(\tau_2 - \alpha - \beta x_i)
$$

\n
$$
Pr(y_i = n - 1|x_i) = \Phi(\tau_n - \alpha - \beta x_i) - \Phi(\tau_{n-1} - \alpha - \beta x_i)
$$

\n
$$
Pr(y_i = n|x_i) = 1 - \Phi(\tau_{n-1} - \alpha - \beta x_i)
$$
\n(4.10)

where *i* is an individual; 1, 2, 3…*n*-1, *n* are response alternatives; $\Phi(\cdot)$ is the standard normal cumulative distribution function.

Since y^* is latent, its mean and variance cannot be estimated. The variance is identified by using that $Var(\varepsilon|x) = 1$. While these assumptions identify the variance, the mean of *y*^{*} is still unidentified. The consequences of this can be seen by considering the model $y^* = \alpha + \beta x + \varepsilon$ with cutpoints τ_m . Think of α and the τ 's as the "true" parameters in the sense that they were used to generate the observed data. Define an alternative set of parameters:

$$
\alpha^* = \alpha - \delta \quad \text{and} \quad \tau_m^* = \tau_m - \delta \tag{4.11}
$$

where τ is an arbitrary constant. The probability that $y = m$ is identical, whether the true or alternative parameters are used:

$$
Pr(y = m|x) = F(\tau_m - \alpha - x\beta) - F(\tau_{m-1} - \alpha - x\beta)
$$

= $F([\tau_m - \delta] - [\alpha - \delta] - \beta x) - F([\tau_{m-1} - \delta] - [\alpha - \delta] - \beta x)$
= $F(\tau_{m-1}^* - \alpha^* - x_i\beta) - F(\tau_{m-1}^* - \alpha^* - x_i\beta)$ (4.12)

Since both sets of parameters generate the same value for the probability of an observed outcome, there is no way to choose between the two sets of parameters using the observed data: a change in the intercept in the structural model can always be compensated for by a corresponding change in the thresholds. That is to say, the model is unidentified.

While there are an infinite number of assumptions that could be made to identify the model, only two are commonly used:

(1). Assume that $\tau_1 = 0$. This involves setting $\delta = \tau_1$ in Equation 4.11.

(2). Assume that $\alpha = 0$. This involves setting $\delta = \alpha$ in Equation 4.11.

Both assumptions identify the model by imposing a constraint on one of the parameters. The different identifying assumptions lead to what are known as different parameterizations of the model. The choice of which parameterization to use is arbitrary and does not affect the β 's (except for β_0) or associated significance tests. Further, as known by Equation 4.12, the probabilities are not affected by the identifying assumption. However, understanding the different parameterizations is important since different software uses different parameterizations. Programs such as LIMDEP uses the first assumption, while programs such as Markov, SAS's LOGISTIC, and Stata use the second

one. The choice of parameterization does not affect estimates of the slopes, but does affect the estimates of β_0 and the τ 's.

4.1.3 Criteria for Ordered Probit Models

4.1.3.1. z - Test

z - Test is used to test the statistical significance of individual estimated coefficient in ordered porbit models. Maximum likelihood estimators possess a number of desirable properties when certain general conditions apply. Independent and identically distributed observations, and independence of the x_i and the model errors (the ε_i) are all that is required. With these conditions satisfied, the maximum likelihood estimator is asymptotically unbiased (consistent), is normally distributed, and has the smallest variance among all consistent and asymptotically normal estimators. The $t -$ ratios for the null hypothesis H_0 that $\beta_i = 0$, and the test statistic is

$$
z = \frac{\hat{\beta}_i}{\hat{\sigma}_i / \sqrt{k}}\tag{4.11}
$$

where $\hat{\beta}_i$ is the estimator of β_i ; and β_i is the *i*th coefficient of the model; $\hat{\sigma}_i$ is the estimator of standard deviation of the coefficient β_i ; *i* is number of observations. If H_0 is true, the coefficient β_i of the model is not statistically significant. If H_0 is rejected at a confidence level (usually is 0.05), the coefficient β_i is significant to the response.

4.1.3.2. Pseudo - R^2

A Pseudo - R^2 is often used as a goodness-of-fit measure in non-linear models. They look like R^2 in the sense that they are on a similar scale, ranging from 0 to 1, but they cannot be interpreted as one would interpret an ordinary least squares (OLS) R^2 and different Pseudo - R^2 can arrive at very different values.

Here, the Pseudo - R^2 is provided as

$$
R^2 = 1 - \frac{\ln \hat{L}(M_{\text{full}})}{\ln \hat{L}(M_{\text{intercept}})}
$$
(4.12)

where *M*_{*full*} is the model with predictors; *M*_{int *ercept*} is the model without predictors; \hat{L} is the estimated likelihood.

A likelihood falls between 0 and 1, so the log of a likelihood is less than or equal to zero. If a model has a very low likelihood, then the log of the likelihood will have a larger magnitude than the log of a more likely model. Thus, a small ratio of log likelihoods indicates that the full model is a far better fit than the intercept model.

4.1.3.3. Likelihood Ration (LR) Test

The likelihood ratio test is a statistical test of the goodness-of-fit between two models. It relies on a test statistic computed by taking the ratio of the maximum value of the likelihood function under the constraint of the null hypothesis to the maximum with that constraint relaxed. The null hypothesis is $H_0: \beta = 0$, where β is the intercept. This statistic is given as

$$
G^{2} = -2[\ln L(M_{\text{constrained}}) - \ln L(M_{\text{unconstrained}})]
$$
\n(4.13)

where $L(M_{\text{constrained}})$ is the likelihood of the constrained model; $L(M_{\text{unconstrained}})$ is the likelihood of the unconstrained model.

This LRT statistic approximately follows a chi-square distribution. The degree of freedom is equal to the number of additional parameters in the unconstrained model. If the null hypothesis is rejected (the confidence level is usually 0.05), it can be concluded that at least one independent variable has significant influence for the dependent variable.

4.1.4 Interpretation of Model Coefficients

4.1.4.1. The Partial Change in y^*

In the ordered regression model,

$$
y^* = x\beta + \varepsilon \tag{4.16}
$$

and the partial change in y^* with respect to x_k is

$$
\frac{\partial y^*}{\partial x_k} = \beta_k \tag{4.17}
$$

Since the model is linear in y^* , the partial change can be interpreted as: for a unit increase in x_k , y^* is expected to change by β_k units, holding all other variables constant. Because the variance of y^* cannot be estimate from the observed data, the meaning of a change of β_k units in y^* is unclear. Interpretations should be based on [∗] *y* -standardized coefficients.

If σ_{y^*} is the unconditional standard deviation of the latent y^* , then the *y*[∗]-standardized coefficient for *x*_{*k*} is

$$
\beta_k^{Sy^*} = \frac{\beta_k}{\sigma_{y^*}}
$$
\n(4.18)

which can be interpreted as: for a unit increase in x_k , y^* in expected to increase by $\beta_k^{S_y^*}$ standard deviations, holding all other variables constant.

y^{*}-standardized coefficients indicate the effect of an independent variable in its original unit of measurement. This is sometimes preferable for substantive reasons and is necessary for binary independent variables.

The variance of y^* can be estimated by the quadratic form:

$$
\hat{\sigma}_{y^*}^2 = \hat{\beta}' \hat{\text{Var}}(x)\hat{\beta} + \text{Var}(\varepsilon)
$$
\n(4.19)

where $\hat{V}ar(x)$ is the covariance matrix for the *x*'s computed from the observed data; $\hat{\beta}$ contains Maximum Likelihood (ML) estimates; and Var (ε) = 1 in the ordered probit model.

4.1.4.2. Partial Change in Predicted Probabilities

The predicted probability that $y = m$ given x is

$$
Pr(y = m|x) = F(\tau_m - x\beta) - F(\tau_m - x\beta)
$$
\n(4.20)

Taking the partial derivative with respect to x_k ,

$$
\frac{\partial \Pr(y = m|x)}{\partial x_k} = \frac{\partial F(\tau_m - x\beta)}{\partial x_k} - \frac{\partial F(\tau_{m-1} - x\beta)}{\partial x_k}
$$

$$
= \beta_k f(\tau_{m-1} - x\beta) - \beta_k f(\tau_m - x\beta)
$$

$$
= \beta_k [f(\tau_{m-1} - x\beta) - f(\tau_m - x\beta)] \tag{4.21}
$$

The partial change or marginal effect is the slope of the curve relating x_k to $Pr(y = m|x)$, holding all other variables constant. The sign of the marginal effect is not necessarily the same as the sign of β , since $f(\tau_{m-1} - x\beta) - f(\tau_m - x\beta)$ can be negative. Indeed, it is possible for the marginal effect of x_k to change signs as x_k changes.

In general, the marginal effect does not indicate the change in the probability that would be observed for a unit changes in x_k . However, if an independent variable varies over a region of the probability curve that is nearly linear, the marginal effect can be used to summarize the effect of a unit change in the variable on the probability of an outcome.

4.2 Data Collection

4.2.1 Data Base

The dataset used to fit the ordered probit model was extracted from the Florida Crash Analysis Reporting (CAR) system. CAR system is a relational database for State System crashes consisting of nine tables which contain different data relevant to a certain facet of a traffic crash (Table 4.2). It maintains electronic crash records based on crashes reported on the long-form crash report. That the variable "FIRST ROAD CONDITION

CRASH COD" is equal to 04 (road under repair/construction) is used as the indicator of work zone crashes. In this study, the work zone crash dataset contained all the work zone crashes from 2002 to 2006.

Some variables in the database were selected for modeling. They may include ordinal variables, nominal variables, or continuous variables. In order to get better result performance all categorical variables should be purposely converted to binary ones (dummy variable). The continuous variables need to be normalized (by dividing by each maximum value) to have values which lie between 0 and 1. The reason for this is that the dummy variables have means between 0 and 1, and ordered multiple choice models are almost never estimable if the variables are of very different magnitudes (Greene 1993). All the missing values are deleted from database. Appendix A lists the description of every original variable in this work zone crashes database.

| File Name | Description |
|----------------|--|
| | Contains information about the crash event (i.e. date, time, harmful events, |
| Events | etc.). This is the "parent file" of the database. |
| Drivers | Contains information about each driver involved in the crash demographic |
| | and causal). |
| | Contains information about each passenger involved in the crash |
| Passengers | (demographic and causal). |
| Pedestrians | Contains information about each pedestrian involved in the crash |
| | (demographic and causal). |
| | Contains information about property (other than vehicles) damaged in the |
| Property | crash. |
| Vehicles | Contains information about each vehicle involved in the crash. |

Table 4.2 Tables from Florida Traffic Crash Records Database

| File Name | Description |
|-------------------|--|
| Violations | Contains information about citations issued to drivers or pedestrians |
| | involved in crashes (limited to the first eight citations issues per party). |
| ComVeh | The newest table, contains information about commercial vehicles and |
| | carriers involved in crashes. |
| DOT | Contains Department of Transportation location and road data. |

Table 4.2 (Continued)

4.2.2 Data Description

For developing the work zone crash injury severity model, 10 variables (Table 4.3) are selected. The dependent variable is the crash injury severity which has 5 levels from no injury to fatal injury at an ascending order. The other independent variables can be categorized as 4 classes: environmental condition, roadway condition, driver's condition, and crash-related information.

| Variable | Description | Type | Value | Definition | | | |
|-------------------|--|---------------|----------------|------------------------------|--|--|--|
| | | | 1 | No Injury | | | |
| | | | $\overline{2}$ | Possible Injury | | | |
| ACCISEV | Crash Severity Level | Ordinal | 3 | Non-incapacitating injury | | | |
| | | | 4 | Incapacitating Injury | | | |
| | | | 5 | Fatal Injury | | | |
| | Environmental Condition | | | | | | |
| | If the crash occurred under the | | Ω | N ₀ | | | |
| LGHTCOND | good lighting condition (daylight) condition) | Binary | 1 | Yes | | | |
| Roadway Condition | | | | | | | |
| CURVE | If there is a curve at the crash | | Ω | N ₀ | | | |
| | location | Binary | 1 | Yes | | | |

Table 4.3 Description of Selected Variables for Model Development

| URBAN | If the crash occurred in a urban | | θ | N ₀ | | | | | |
|---------------------------|---|---------------|----------------|------------------|--|--|--|--|--|
| | area | Binary | 1 | Yes | | | | | |
| MAXSPEED | Maximum Posted Speed Limit | Continuous | | | | | | | |
| SECTADT | Section average annual daily Continuous traffic | | | | | | | | |
| Driver's Condition | | | | | | | | | |
| | | | 1 | Young $(15-24)$ | | | | | |
| AGE_AT_FA ULT | At fault driver's age | Categorical | $\overline{2}$ | Middle $(25-64)$ | | | | | |
| | | | 3 | Old $(≥65)$ | | | | | |
| ALDGUSE | If at fault driver was under | | θ | N ₀ | | | | | |
| AT FAULT | influence of alcohol or drugs | Binary | 1 | Yes | | | | | |
| | Crash-Related | | | | | | | | |
| VEHTYPE | If heavy vehicle (heavy truck and | | $\overline{0}$ | N ₀ | | | | | |
| | truck tractor) was involved | Binary | 1 | Yes | | | | | |
| | | | 1 | Rear-end | | | | | |
| HARMEVN | | Categorical | $\overline{2}$ | Angle | | | | | |
| | Crash Type | | 3 | Sideswipe | | | | | |
| | | | 4 | Other Types | | | | | |

Table 4.3 (Continued)

Table 4.4 describes the minimum value, maximum value, range, mean, and standard deviation of the two continuous variables. The minimums, maximums, ranges, means, and standard deviations of the original unnormalized variables can be obtained easily by multiplying the values in Table 4.4 by the appropriate scaling factors (the original maximum values in each variable). The range of AADT in work zone area is very large from $0.0045 \times 289,000 = 1,300$ vehicles per day to $1 \times 289,000 = 289,000$ vehicles per day. The minimum speed limit is $0.2143 \times 70 = 15$ miles per hour, the maximum one is $1 \times 70 = 70$ miles per hour, and mean value is $0.7455 \times 70 = 52$ miles per hour.

| Varibale | | | Minimum Maximum | Range | Mean | Std. Deviation Factors | Scaling |
|-----------------|-------|--------|-------------------|--------|--------|---------------------------|---------|
| SECADT | 14217 | 0.0045 | | 0.9955 | 0.2205 | 0.1774 | 289000 |
| MAXSPEED | 14217 | 0.2143 | | 0.7857 | 0.7455 | 0.15984 | 70 |

Table 4.4 Description Statistic of Continuous Variables

Table 4.5 illustrates the discrete variables' frequency statistic. When the crash injury severity increases, the frequency of crashes decreases. The total percentage of slight injury crashes ($\text{ACCISEV} = 1, 2, \text{ and } 3$) in work zone area is 90.41%. Incapacitating injury crash only holds 7.94%, and the fatal crash has the least proportion which is 1.66%. More than one third of work zone crashes (34.17%) occur under the not good lighting condition (non-daylight), and 85.84% of them in the urban area. Only 8.10% of locations where work zone crash happen has curve, 14.62% work zone crashes occur with heavy vehicle involvement, and 5.15% drivers are influenced by drugs or alcohol.

The top three crash types here are rear-end (37.15%), angle (12.04%), and sideswipe (11.26%). The distribution of at-fault driver's age group is 23.61% young age drivers, 66.81% middle age drivers, and 9.59% old age drivers.

| Variable | Value Frequency | | | |
|------------------|--------------------|-------|-------|--|
| | Sample Size 14217 | | | |
| | $\mathbf{1}$ | 6477 | 45.56 | |
| | $\overline{2}$ | 3555 | 25.01 | |
| ACCISEV | \mathfrak{Z} | 2820 | 19.83 | |
| | $\overline{4}$ | 1129 | 7.94 | |
| | 5 | 236 | 1.66 | |
| | | | | |
| | | | | |
| LGHTCOND | $\boldsymbol{0}$ | 4858 | 34.17 | |
| | $\mathbf{1}$ | 9359 | 65.83 | |
| | | | | |
| CURVE | $\boldsymbol{0}$ | 13065 | 91.90 | |
| | $\mathbf{1}$ | 1152 | 8.10 | |
| | | | | |
| URBAN | $\boldsymbol{0}$ | 2013 | 14.16 | |
| | $\mathbf{1}$ | 12204 | 85.84 | |
| | | | | |
| | $\mathbf{1}$ | 3356 | 23.60 | |
| AGE_AT_FAULT | $\sqrt{2}$ | 9498 | 66.81 | |
| | 3 | 1363 | 9.59 | |
| | | | | |
| ALDGUSE_AT_FAULT | $\boldsymbol{0}$ | 13485 | 94.85 | |
| | $\mathbf{1}$ | 732 | 5.15 | |
| | | | | |
| VEHTYPE | $\boldsymbol{0}$ | 12139 | 85.38 | |
| | $\mathbf{1}$ | 2078 | 14.62 | |
| | | | | |
| | $\mathbf{1}$ | 5282 | 37.15 | |
| HARMEVN | $\sqrt{2}$ | 1712 | 12.04 | |
| | 3 | 1601 | 11.26 | |
| | $\overline{4}$ | 5622 | 39.55 | |
| | | | | |

Table 4.5 Frequencies of Discrete Variables

4.3 Work Zone Crash Injury Severity Model

4.3.1 Estimation Procedure

This section presents the estimation results of the work zone crash severity model for all work zone crashes. At first, cross tabulation analysis is performed to check the distribution of explanatory variables across injury severity levels and ensure enough observations in each cell. And AGE_AT_FAULT variable was transformed to three dummy variables: YOUNG_AGE (AGE_AT_FAULT = 1), MIDDLE_AGE $(AGE_AT_FAULT = 2)$, and $OLD_AGE (AGE_AT_FAULT = 3)$. Be similar, another categorical variable HARMEVN was converted to four dummy variables: REAR-END $(HARMEVN =1)$, $ANGLE (HARMEVN = 2)$, $SIDESWIPE (HARMEVN = 3)$, and OTHERS (HARMEVN $= 4$). After then, the ordinal probit regression model was developed using the OPROBIT procedure in the STATA software package. In the procedure, the stepwise option was added for selecting independent variables for which the significant level is greater than 95%. The theory of variable selection is: at first, there was no variable in this ordered probit model, then the variables whose p-value is less or equal to 0.05 were added into the model one by one.

4.3.2 Cross Tabulations between Explanatory Variables and Crash Severity

In order to obtain a better understanding about the selected explanatory variables, cross tabulations of binary or categorical variables with crash severity were developed and given in Tables 4.6.

| Frequency Row % | Value | $\mathbf{1}$ | $\overline{2}$ | 3 | $\overline{4}$ | 5 | Total |
|---------------------|----------------|--------------|----------------|-------|----------------|------|-------|
| | | 2131 | 1118 | 1013 | 452 | 144 | 4858 |
| | $\overline{0}$ | 43.9% | 23.0% | 20.9% | 9.3% | 3.0% | 100% |
| | $\mathbf{1}$ | 4346 | 2437 | 1807 | 677 | 92 | 9359 |
| LGHTCOND | | 46.4% | 26.0% | 19.3% | 7.2% | 1.0% | 100% |
| | Total | 6477 | 3555 | 2820 | 1129 | 236 | 14217 |
| | | 45.6% | 25.0% | 19.8% | 7.9% | 1.7% | 100% |
| | $\overline{0}$ | 5950 | 3316 | 2574 | 1016 | 209 | 13065 |
| | | 45.5% | 25.4% | 19.7% | 7.8% | 1.6% | 100% |
| CURVE | | 527 | 239 | 246 | 113 | 27 | 1152 |
| | $\mathbf{1}$ | 45.7% | 20.7% | 21.4% | 9.8% | 2.3% | 100% |
| | Total | 6477 | 3555 | 2820 | 1129 | 236 | 14217 |
| | | 45.6% | 25.0% | 19.8% | 7.9% | 1.7% | 100% |
| | $\overline{0}$ | 787 | 408 | 491 | 252 | 75 | 2013 |
| | | 39.1% | 20.3% | 24.4% | 12.5% | 3.7% | 100% |
| URBAN | $\mathbf{1}$ | 5690 | 3147 | 2329 | 877 | 161 | 12204 |
| | | 46.6% | 25.8% | 19.1% | 7.2% | 1.3% | 100% |
| | Total | 6477 | 3555 | 2820 | 1129 | 236 | 14217 |
| | | 45.6% | 25.0% | 19.8% | 7.9% | 1.7% | 100% |
| | $\mathbf{1}$ | 1391 | 891 | 748 | 267 | 59 | 3356 |
| | | 41.4% | 26.5% | 22.3% | 8.0% | 1.8% | 100% |
| | $\overline{2}$ | 4496 | 2330 | 1795 | 730 | 147 | 9498 |
| AGE AT FAULT | | 47.3% | 24.5% | 18.9% | 7.7% | 1.5% | 100% |
| | 3 | 590 | 334 | 277 | 132 | 30 | 1363 |
| | | 43.3% | 24.5% | 20.3% | 9.7% | 2.2% | 100% |
| | Total | 6477 | 3555 | 2820 | 1129 | 236 | 14217 |
| | | 45.6% | 25.0% | 19.8% | 7.9% | 1.7% | 100% |

Table 4.6 Cross Tabulation between explanatory Variables and Crash Severity

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| | Value | | Total | | | | |
|------------------|----------------|--------------|----------------|-------|----------------|-------|-------|
| Frequency Row % | | $\mathbf{1}$ | $\overline{2}$ | 3 | $\overline{4}$ | 5 | |
| | $\mathbf{1}$ | 2110 | 1782 | 1043 | 314 | 33 | 5282 |
| | | 39.9% | 33.7% | 19.7% | 5.9% | 0.6% | 100% |
| | | 708 | 410 | 388 | 172 | 34 | 1712 |
| | $\overline{2}$ | 41.4% | 23.9% | 22.7% | 10.0% | 2.0% | 100% |
| HARMEVN | 3 | 1183 | 226 | 144 | 43 | 5 | 1601 |
| | | 73.9% | 14.1% | 9.0% | 2.7% | 0.3% | 100% |
| | | 2476 | 1137 | 1245 | 600 | 164 | 5622 |
| | $\overline{4}$ | 44.0% | 20.2% | 22.1% | 10.7% | 2.9% | 100% |
| | | 6477 | 3555 | 2820 | 1129 | 236 | 14217 |
| | Total | 45.6% | 25.0% | 19.8% | 7.9% | 1.7% | 100% |
| | $\overline{0}$ | 6140 | 3445 | 2696 | 1050 | 154 | 13485 |
| | | 45.5% | 25.5% | 20.0% | 7.8% | 1.1% | 100% |
| ALDGUSE_AT_FAULT | $\mathbf{1}$ | 337 | 110 | 124 | 79 | 82 | 732 |
| | | 46.0% | 15.0% | 16.9% | 10.8% | 11.2% | 100% |
| | Total | 6477 | 3555 | 2820 | 1129 | 270 | 14251 |
| | | 45.4% | 24.9% | 19.8% | 7.9% | 1.9% | 100% |
| | $\overline{0}$ | 5141 | 3223 | 2553 | 1030 | 192 | 12139 |
| | | 42.4% | 26.6% | 21.0% | 8.5% | 1.6% | 100% |
| VEHTYPE | $\mathbf{1}$ | 1336 | 332 | 267 | 99 | 44 | 2078 |
| | | 64.3% | 16.0% | 12.8% | 4.8% | 2.1% | 100% |
| | Total | 6477 | 3555 | 2820 | 1129 | 236 | 14217 |
| | | 45.6% | 25.0% | 19.8% | 7.9% | 1.7% | 100% |

Table 4.6 (Continued)

4.3.3 Estimation Results

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The estimation of results of the ordinal probit regression is given in Table 4.7. The sample size is 14,217 observations, and the Likelihood Ratio (LR) test statistic falls into the rejection area $(p - value = 0 < 0.05)$. That means the overall explanatory variables of the model have significant influence on the responses (crash severity levels) at a statistical significance level 95%. Except for ANGLE, all slope coefficients are significant at a confidence level 0.05. Although the *p - value* of ANGLE is little greater

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than 0.05, the variable was still included in the model since angle crash was an important

crash type and more variables increase the explanation ability of the model.

| Table 4.7 Estimation of Ordered Probit Regression for Work Zone Crash Severity Model | | | | | | | | |
|--|-----------|-----------|---------------------------------|-----------|------------------------|-----------|--|--|
| Ordered probit regression | | | Number of observation = 14217 | | | | | |
| | | | LR chi $2(12) = 1094.6$ | | | | | |
| | | | | | Prob > chi $2 = 0.000$ | | | |
| Log likelihood = -17861.331 | | | | Pseudo R2 | $= 0.0297$ | | | |
| ACCISEV | Coef. | Std. Err. | Z | P > z | [95% Conf.Interval] | | | |
| LGHTCOND | -0.0981 | 0.0206 | -4.77 | 0.000 | -0.1384 | -0.0578 | | |
| CURVE | 0.0818 | 0.0344 | 2.38 | 0.018 | 0.01432 | 0.1494 | | |
| URBAN | -0.1768 | 0.0308 | -5.74 | 0.000 | -0.2372 | -0.1164 | | |
| VEHTYPE | -0.3846 | 0.0295 | -13.02 | 0.000 | -0.4425 | -0.3267 | | |
| ALDGUSE_AT_FAULT | 0.2096 | 0.0430 | 4.87 | 0.000 | 0.1252 | 0.2939 | | |
| YOUNG_AGE | 0.0506 | 0.0224 | 2.26 | 0.024 | 0.0067 | 0.0945 | | |
| OLD_AGE | 0.1229 | 0.0326 | 3.77 | 0.000 | 0.0590 | 0.1867 | | |
| REAR-END | -0.0752 | 0.0217 | -3.47 | 0.001 | -0.1178 | -0.0327 | | |
| ANGLE | 0.0569 | 0.0305 | 1.87 | 0.062 | -0.0028 | 0.1166 | | |
| SIDESWIPE | -0.7253 | 0.0363 | -19.98 | 0.000 | -0.7964 | -0.6541 | | |
| SECADT | -0.3851 | 0.0656 | -5.87 | 0.000 | -0.5136 | -0.2565 | | |
| MAXSPEED | 0.7702 | 0.0742 | 10.38 | 0.000 | 0.6248 | 0.9156 | | |
| /cutpoint1 | 0.0434 | 0.0677 | | | -0.0892 | 0.1761 | | |
| /cutpoint2 | 0.7261 | 0.0679 | | | 0.5931 | 0.8591 | | |
| /cutpoint3 | 1.5236 | 0.0686 | | | 1.3892 | 1.6579 | | |
| /cutpoint4 | 2.3867 | 0.0722 | | | 2.2452 | 2.5281 | | |

Table 4.7 Estimation of Ordered Probit Regression for Work Zone Crash Severity Model

Based on the estimated results in Table 4.7, the probability models for five crash injury severity levels are given as:

$$
Pr(y_i = 1|x_i) = \Phi(\tau_1 - \beta x_i)
$$

\n
$$
Pr(y_i = 2|x_i) = \Phi(\tau_2 - \beta x_i) - \Phi(\tau_1 - \beta x_i)
$$

\n
$$
Pr(y_i = 3|x_i) = \Phi(\tau_3 - \beta x_i) - \Phi(\tau_2 - \beta x_i)
$$

\n
$$
Pr(y_i = 4|x_i) = \Phi(\tau_4 - \beta x_i) - \Phi(\tau_3 - \beta x_i)
$$

\n
$$
Pr(y_i = 5|x_i) = 1 - \Phi(\tau_4 - \beta x_i)
$$
\n(4.22)

where τ is the cutpoint, and β is the coefficient of the corresponding variable.

4.3.4 Interpretation

The crash severity model estimated by the ordinal probit regression has the same slope coefficients across all severity levels. For example, the coefficient for LGHTCOND is -0.0981 and the standardized coefficient for it is -0.0931, which means that the presence of day light $(LGHTCOND = 1)$ tends to reduce the injury severity of work zone crashes, and when driving in daylight condition, the probability of having a higher injury severity crash is 0.0931 standard deviations lower than in non-daylight condition, holding all other variables constant. Table 4.8 and 4.9 shows the estimated results of the partial changes in *y*^{*} and in predicted probabilities for this ordered model respectively.

| ACCISEV | Coef. | Z | P > z | y standardized coef. |
|------------------|-----------|----------|-------|----------------------|
| LGHTCOND | -0.0981 | -4.773 | 0.000 | -0.0931 |
| CURVE | 0.0818 | 2.38 | 0.018 | 0.0777 |
| URBAN | -0.1768 | -5.74 | 0.000 | -0.1678 |
| VEHTYPE | -0.3846 | -13.02 | 0.000 | -0.3650 |
| ALDGUSE AT FAULT | 0.2096 | 4.87 | 0.000 | 0.1989 |
| YOUNG AGE | 0.0506 | 2.26 | 0.024 | 0.0480 |
| | | | | |

Table 4.8 Partial Change in *y* *

| OLD AGE | 0.1229 | 3.77 | 0.000 | 0.1166 |
|------------------|-----------|----------|-------|-----------|
| REAR-END | -0.0752 | -3.47 | 0.001 | -0.0714 |
| ANGLE | 0.0569 | 1.87 | 0.062 | 0.0541 |
| SIDESWIPE | -0.7253 | -19.98 | 0.000 | -0.6882 |
| SECADT | -0.3851 | -5.87 | 0.000 | -0.3654 |
| MAXSPEED | 0.7702 | 10.38 | 0.000 | 0.7308 |

Table 4.8 (Continued)

Table 4.9 Partial Change in Predicted Probabilities

| | | Possible | Non-incapacitating | Incapacitating | Fatal |
|------------------|-----------|-----------|--------------------|----------------|-----------|
| | No Injury | Injury | Injury | Injury | Injury |
| LGHTCOND | 0.0388 | -0.0053 | -0.0179 | -0.0123 | -0.0034 |
| P > z | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| CURVE | -0.0323 | 0.0040 | 0.0149 | 0.0105 | 0.0029 |
| P > z | 0.017 | 0.005 | 0.017 | 0.022 | 0.029 |
| URBAN | 0.0694 | -0.0074 | -0.0318 | -0.0234 | -0.0068 |
| P > z | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| VEHTYPE | 0.1524 | -0.0333 | -0.0693 | -0.0403 | -0.0096 |
| P > z | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ALDGUSE_AT_ | -0.0817 | 0.0072 | 0.0374 | 0.0286 | 0.0086 |
| FAULT | | | | | |
| P > z | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| YOUNG AGE | -0.0200 | 0.0027 | 0.0092 | 0.0063 | 0.0017 |
| P > z | 0.024 | 0.017 | 0.024 | 0.026 | 0.030 |
| OLD_AGE | -0.0483 | 0.0056 | 0.0222 | 0.0160 | 0.0045 |
| P > z | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 |
| REAR-END | 0.0299 | -0.0045 | -0.0137 | -0.0092 | -0.0024 |
| P > z | 0.001 | 0.001 | 0.001 | 0.000 | 0.000 |
| ANGLE | -0.0225 | 0.0030 | 0.0104 | 0.0072 | 0.0020 |
| P > z | 0.061 | 0.039 | 0.061 | 0.068 | 0.076 |
| SIDESWIPE | 0.2793 | -0.0792 | -0.1231 | -0.0632 | -0.0138 |
| P > z | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| SECADT | 0.1527 | -0.0222 | -0.0703 | -0.0475 | -0.0127 |
| P > z | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| MAXSPEED | -0.3054 | 0.0443 | 0.1406 | 0.0950 | 0.0255 |
| P > z | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

4.3.4.1. Signs

In the Tables 4.8, the variables recording daylight condition, urban area, heavy vehicle involved, rear-end crash type, sideswipe crash type and average annual daily traffic have negative coefficients, that means when the value of these variables increase, the crash injury severity is more likely to be slight. In contrast, the increase of other variables with positive coefficients tends to make a higher probability of more severe injury crashes. The summary is in Table 4.10

| Independent Variable | Sign | Influence for Crash Severity Level | |
|-----------------------------|--------|---|--|
| LGHTCOND | | Decrease | |
| CURVE | $^{+}$ | Increase | |
| URBAN | | Decrease | |
| VEHTYPE | | Decrease | |
| ALDGUSE_AT_FAULT | $^{+}$ | Increase | |
| YOUNG_AGE | $^{+}$ | Increase | |
| OLD_AGE | $^{+}$ | Increase | |
| REAR-END | | Decrease | |
| ANGLE | $^{+}$ | Increase | |
| SIDESWIPE | | Decrease | |
| SECADT | | Decrease | |
| MAXSPEED | | Increase | |

Table 4.10 Analysis of the Coefficient Signs

4.3.4.2. Magnitude of Coefficients

The injury severity level y^* is specified as a linear function of the independent variables, the relative magnitudes of estimated variable coefficients are, in most cases, a measure of the relative impacts of these variables on the average severity level of injury

severity (O'Donnell and Connor, 1996). For example, the increase in injury severity of an old driver is about 2.43 times higher than the increase in injury severity of a young driver, all other things being equal, because the estimated coefficient of the variable OLD_AGE $(\hat{\beta} = 0.1229)$ is about 2.43 larger than the estimate of the coefficient of the variable YOUNG_AGE ($\hat{\beta} = 0.0506$). Then, the estimated variable coefficients can be compared in this way and the influences of different variables on average injury severity level can be ranked (see Table 4.11).

| Rank | Independent | Coefficient | Independent | Coefficient |
|-----------------------------|-----------------|-------------|------------------|-------------|
| | Variable | (Positive) | Variable | (Negative) |
| | MAXSPEED | 0.7702 | SIDESWIPE | -0.7253 |
| $\mathcal{D}_{\mathcal{L}}$ | ALDGUSE_AT_ | 0.2096 | SECADT | -0.3851 |
| | FAULT | | | |
| 3 | OLD AGE | 0.1229 | VEHTYPE | -0.3846 |
| 4 | CURVE | 0.0818 | URBAN | -0.1768 |
| 5 | ANGLE | 0.0569 | LGHTCOND | -0.0981 |
| | YOUNG AGE | 0.0506 | REAR-END | -0.0752 |

Table 4.11 Ranked Magnitudes of Coefficients

4.3.4.3. Detailed Interpretations

(1) Under good lighting conditions (such as daylight), the work zone crash severity is more likely to decrease.

(2) A curved design at the work zone sections, which means the driving condition

turns to be difficult, is easily to result in a severe sever crash.

(3) In urban work zone area, the level of crash injury tends to decrease. It may

because of the lower driving speed.

(4) Heavy vehicle involved can induce to less sever crashes. This is not the same as we think usually. The reason might be that the most people drive carefully when there is a truck around them.

(5) Alcohol and drugs tend to increase the crash injury severity level.

(6) In two special age groups, young age drivers who are more aggressive and have less experience and old age drivers whose physical, visual, and cognitive abilities may deteriorate are easily involved into severe crashes. But the influence of the old age is more than which of the young age.

(7) Two major crash types in work zone area, read-end and sideswipe may not contribute directly hurt to drivers, so if these two types of crashes happen, the probability of having injury would decrease. The condition of angle crash type occurring is totally contrary. The impact of the sideswipe crashes is much more than the impact of the rear-end crashes $(0.7253 / 0.0752 = 9.64)$.

(8) The increase of maximum speed limit tends to increase the crash severity level and the condition is totally contrary to the variable AADT.

(9) According to the different magnitudes of estimated variable coefficients, the increase of maximum posted speed ($\hat{\beta} = 0.7702$) has the highest impact to increase the crash severity level, which is the 3.67 times higher than the second ranked variable ALDGUSE_AT_FAULT ($\hat{\beta} = 0.2096$). In contrast, the sideswipe crash type $(\hat{\beta} = -0.7253)$ has the highest impact to reduce the crash severity level, which is the 1.88

times higher than the second ranked variables SECADT ($\hat{\beta} = -0.3851$), and VEHTYPE $(\hat{\beta} = -0.3846)$.

4.3.5 Possible Countermeasures to Improve Work Zone Safety

Since the explanatory variables are the factors which have significant influence on the crash severity, the countermeasures can be suggested based on the variables in the models.

(1) Driving in daylight can reduce crash severity level, so a good lighting condition is important for work zone safety, especially during the nighttime periods. When nighttime work is being performed, floodlights should be used to illuminate in work zones, but the disabling glare condition for approaching road users which might be produced should be noticed.

(2) Be careful the work zone transition beginning in existing horizontal curve. We can keep continuous curve radii on work zone transitions which can help drivers from overestimating the appropriate speed, resulting in fewer runoff-the-road crashes, or move transition upstream so that it does not start in an existing horizontal curve instead.

(3) Speed limit is to keep drivers at a constant safe speed in work zones. Several other signs besides regular speed limit sign such as speed feedback signs and changeable message signs with radar (CMR) can be used.

Speed feedback signs usually measure using radar and display an individual vehicle's speed. These signs can only display speed, but several have the capability of displaying other text, such as "Slow Down."

CMR displays warning messages when a vehicle is traveling at an unsafe speed. The standard message on the CMS unit changes when a vehicle is traveling faster than the programmed speed, typically 3 mph above the speed limit. The messages used might included: "YOU ARE SPEEDING, SLOW DOWN," "HIGH SPEED, SLOW DOWN," "REDUCE SPEED IN WORK ZONE," and "EXCESSIVE SPEED, SLOW DOWN."

CHAPTER FIVE

SUMMARY

5.1 Summary

The main objectives of this study are to investigate the characteristics of accidents in work zones, to identify the factors contributing to injury severity levels, and to study how the factor influence injury levels. To achieve this purpose, two different statistics are processed. One is descriptive statistics and the other ordered regression modeling.

Descriptive statistic analysis was used to get the distribution of work zone crashes over three age groups for various factors which were paid attentions by researchers. In this part, crash severity level, environmental conditions, crash types, contributing factors, heavy vehicle involvement, and alcohol/drugs involvement were discussed over age groups, in some characteristics even the distribution between work zone and non-work zone were compared. The main results are:

(1) In work zone area, the middle age drivers cause the highest proportion (67%) of crashes, while in non-work zone area they have a lower possibility of occurring crashes (63%).

(2) Middle age drivers involved the highest percentage in the no injury crashes which is 49%, and always has the lowest one in other crashes. While in the more severe level crashes, elderly drivers contribute more than the other two age groups

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(3) Rear-end, angle and sideswipe are the principle crash types in all three age groups. In young and middle age groups, the percentage of rear-end crashes is obviously higher than angle and sideswipe crashes, and elderly age group shows higher rate in angle crashes than others. Read-end and sideswipe crashes are more likely to be occurred in work zone area.

(4) The most predominant factor for work zone crashes is careless driving, and others are failed to yield right of way, no improper driving action and improper lane change in all age groups. But in elderly age group, the distribution (proportion and rank) has slight difference. In the distribution of predominant contributing factors over the principal crash types, careless driving, failed to yield right of way, and improper lane change are three most predominant contributing factor for rear-end, angle, and sideswipe crashes respectively.

(5) Heavy vehicle is more easily related to work zone crashes (14%) than non-work zone crashes (7%). Most driver especially old driver is not influenced by alcohol/drugs.

Crash severity is an important criterion reflecting the cost of work zone crashes in social and economy, and affected by various factors including driver's characteristics, vehicle characteristics, environmental factors, and roadway features. A full understanding of the impacts of the factors on the crash severity is beneficial to select proper countermeasure for reducing the crash severity at work zones and decrease the loss of construction/maintenance on roadway. A probit regression for ordinal output was used to

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estimate the crash severity models for overall work zone crashes. Based on the results of crash severity modeling and analysis, some conclusions can be obtained:

(1) According to the ordered probit model for work zone crash severity, lighting condition, road section with curves, urban or rural area, heavy vehicle involved, alcohol/drug involvement, young and old age group, three predominant crash types, AADT and maximum posted speed have the main influence to work zone crash severity.

(2) The factors of daylight condition, urban, rear-end crash type, sideswipe crash type and high average annual daily traffic are more likely to reduce the severity of work zone crashes.

(3) In contrast to the common sense, heavy vehicle involved could induce work zone crash severity. That's maybe because of driving carefully when there is a truck or tractor around.

(4) Based on the magnitudes of the variable coefficients, the variables of maximum posted speed and the sideswipe crash have the major impact to crash severity level. That shows restriction to driving speed is principle factor for work zone safety.

Based on these statistical analyses for work zone crashes, several countermeasures can be given:

(1) Floodlights needs to be used to illuminate in work zones in the nighttime in order to build a good lighting condition.

(2) Discourage traffic control plan designs that include transition areas for the work

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zone on an existing horizontal curve, and encourage that the transition be accomplished on a tangent section instead.

(3) Speed limit signs are very important for work zone safety. Some dynamic signs like changeable message signs with radar and speed feedback signs have better effectiveness to reduce driver speed.

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APPENDICES

Appendix A: Variables and Codes of Work Zone Crash Table A-1 Variable of Work Zone Crashes

Table A-2 Codes for TIME

| Codes | Description |
|-------|-------------|
| | $<$ 19 |
| | 20-24 |
| | 25-34 |
| | 35-44 |
| | 45-54 |
| | $55 - 64$ |
| | >65 |

Table A-3 Codes for AGE

Table A-4 Codes for VEHMOVEMENT

| Codes | Description |
|-------|---------------------------------------|
| 01 | STRAIGHT AHEAD |
| 02 | SLOWING/STOPPED/STALLED |
| 03 | MAKING LEFT TURN |
| 04 | BACKING |
| 05 | MAKING RIGHT TURN |
| 06 | CHANGING LANES |
| 07 | ENTERING/LEAVING PARKING SPACE |
| 08 | PROPERLY PARKED |
| 09 | IMPROPERLY PARKED |
| 10 | MAKING U-TURN |
| 11 | PASSING |
| 12 | DRIVERLESS OR RUNAWAY VEH. |
| 77 | ALL OTHERS |
| 88 | UNKNOWN |

| Codes | Description | |
|-------|--------------------------------------|--|
| 01 | COLL. W/MV IN TRANS. REAR-END | |
| 02 | COLL. W/MV IN TRANS. HEAD-ON | |
| 03 | COLL. W/MV IN TRANS. ANGLE | |
| 04 | COLL. W/MV IN TRANS. LFT-TURN | |
| 05 | COLL. W/MV IN TRANS. RGT-TURN | |
| 06 | COLL. W/MV IN TRANS. SIDESWIP | |
| 07 | COLL. W/MV IN TRANS. BAKD INTO | |
| 08 | COLL. W/PARKED CAR | |
| 09 | COLLISION WITH MV ON ROADWAY | |
| 10 | COLL. W/ PEDESTRIAN | |
| 11 | COLL. W/BICYCLE | |
| 12 | COLL. W/ BICYCLE (BIKE LANE) | |
| 13 | COLL. W/MOPED | |
| 14 | COLL. W/TRAIN | |
| 15 | COLL. W/ ANIMAL | |
| 16 | MV HIT SIGN/SIGN POST | |
| 17 | MV HIT UTILITY POLE/LIGHT POLE | |
| 18 | MV HIT GUARDRAIL | |
| 19 | MV HIT FENCE | |
| 20 | MV HIT CONCRETE BARRIER WALL | |
| 21 | MV HIT BRDGE/PIER/ABUTMNT/RAIL | |
| 22 | MV HIT TREE/SHRUBBERY | |
| 23 | COLL. W/CONSTRCTN BARRICDE/SGN | |
| 24 | COLL. W/TRAFFIC GATE | |
| 25 | COLL. W/CRASH ATTENUATORS | |
| 26 | COLL. W/FIXED OBJCT ABOVE ROAD | |
| 27 | MV HIT OTHER FIXED OBJECT | |
| 28 | COLL. W/MOVEABLE OBJCT ON ROAD | |
| 29 | MV RAN INTO DITCH/CULVERT | |
| 30 | RAN OFF ROAD INTO WATER | |
| 31 | OVERTURNED | |
| 32 | OCCUPANT FELL FROM VEHICLE | |
| 33 | TRACTOR/TRAILER JACKNIFED | |
| 34 | FIRE | |
| 35 | EXPLOSION | |
| 36 | DOWNHILL RUNAWAY | |
| 37 | CARGO LOSS OR SHIFT | |

Table A-5 Codes for CRASHTYPE

Table A-6 Codes for VEHICLETYPE

| Codes | Description |
|-------|---------------------------------|
| 00 | UNKNOWN/NOT CODED |
| 01 | AUTOMOBILE |
| 02 | PASSENGER VAN |
| 03 | PICKUP/LIGHT TRUCK (2 REAR TIR) |
| 04 | MEDIUM TRUCK (4 REAR TIRES) |
| 05 | HEAVY TRUCK (2 OR MORE REAR AX) |
| 06 | TRUCK TRACTOR (CAB) |
| 07 | MOTOR HOME (RV) |
| 08 | BUS (DRIVER $+9 - 15$ PASS) |
| 09 | BUS (DRIVER $+$ > 15 PASS) |
| 10 | BICYCLE |
| 11 | MOTORCYCLE |
| 12 | MOPED |
| 13 | ALL TERRAIN VEHICLE |
| 14 | TRAIN |
| 15 | LOW SPEED VEHICLE |
| 77 | OTHER |
| 88 | PEDESTRIAN NO VEHICLE |

Table A-7 Codes for TRWAYCHR

| Codes | Description |
|-------|--------------------|
| 01 | SLAG/GRAVEL/STONE |
| 02 | BLACKTOP |
| 03 | BRICK/BLOCK |
| 04 | CONCRETE |
| 05 | DIRT |
| | ALL OTHER |

Table A-8 Codes for TYPESUR

Table A-9 Codes for SITELOCA

Table A-10 Codes for LIGHTCONDITION

Table A-11 Codes for WEATHERCONDITION

Table A-12 Codes for ROADSURFACE

| Codes | Description |
|-------|------------------|
| 01 | DRY |
| 02 | WET |
| 03 | SLIPPERY |
| 04 | ICY |
| 77 | ALL OTHER |
| 88 | UNKNOWN |

Table A-13 Codes for VISION

Table A-14 Codes for RDACCESS

Table A-15 Codes for CONTRIBUTINGFACTORS

| Codes | Description |
|-------|------------------------|
| 01 | NO CONTROL |
| 02 | SPECIAL SPEED ZONE |
| 03 | SPEED CONTROL SIGN |
| 04 | SCHOOL ZONE |
| 05 | TRAFFIC SIGNAL |
| 06 | STOP SIGN |
| 07 | YIELD SIGN |
| 08 | FLASHING LIGHT |
| 09 | RAILROAD SIGNAL |
| 10 | OFFICER/GUARD/FLAGMAN |
| 11 | POSTED NO U-TURN |
| 12 | NO PASSING ZONE |
| 77 | ALL OTHER |

Table A-16 Codes for TRAFCONT

