Identifying weather-related factors affecting crash severity and consequent response actions : a comparative analysis of the multinomial logit and ordered probit model forms
by Daniel Thomas Blomquist

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering
Montana State University

Abstract:
This investigation, focused on a mountainous pass corridor in southern Montana, considers the twofold problem of: (1) subjectivity in action-based decision-making related to adverse weather conditions by response personnel and (2) debate over the appropriate statistical form for modeling crash severity.

To address these problems, researchers developed a statistical model relating weather and roadway conditions to crash severity. Interpretation of the model findings were intended to aid response personnel by defining predetermined courses of action dependent on those weather and roadway conditions deemed to result in the lowest levels of safety. Further, modeling severity data with both multinomial logit and ordered probit methods, a direct comparison would allow the most appropriate model form for this application to be determined.

Results of this effort show all model coefficients are plausible in magnitude and direction of effect with both models having reasonable goodness of fit. Independent variables found to have a significant effect on crash severity for the ordered probit model included the year 1999, sideswipe same direction collision type, the presences of right-side guardrail, the presence of a spiral curve, a posted speed limit of 75 mph for cars/65 mph for trucks and wind speed. Independent variables significant in the multinomial logit model are van vehicle type, sideswipe same direction collision type, the presence of right-side guardrail, the presence of a spiral curve, damp roadway surface conditions and wind speed.

The lack of significant weather-related variables in the final models limits the conclusions made to guide action-based decision-making related to adverse weather conditions. Increased wind speed has the effect of decreasing crash severity so no safety-related threshold can be set to guide response activities. Damp roadway surface conditions increase the probability of a more severe crash so it may be justifiable to include damp road warnings with other traditional roadway surface condition warnings given to motorists entering the corridor. Road closures are likely not warranted under these conditions.

The overall agreement in quantitative results between the two model forms used indicates the more appropriate model form must be decided on by qualitative assessments such as ease of use and interpretation of model results. Based on these assessments, the most appropriate statistical form for modeling crash severity is the ordered probit model.

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APPROVAL

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Daniel Thomas Blomquist

This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the College of Graduate Studies.

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ABSTRACT

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CHAPTER 1

INTRODUCTION

> "The impact that traffic crashes have on society is significant. Individuals injured (or killed) in traffic crashes must deal with pain and suffering, medical costs, wage loss, higher insurance premium rates and vehicle repair costs. For society as a whole, traffic crashes result in enormous costs in terms of lost productivity and property damage. Clearly, efforts to improve our understanding of the factors that influence crash severity are warranted (1)."

The relationship between a multitude of risk factors and crash severity has long been a major concern in highway travel safety. One risk factor of special concern, especially in rural areas, is weather condition. Adverse weather can significantly change the condition of the roadway within a short period of time, often with little or no warning to motorists or response personnel charged with protecting the public safety. This Chapter elaborates on the scope of this problem, provides background information related to the SAFE-PASSAGE Project, which this investigation complements, and details this report's content and organization to assist the reader in navigating the document.

Problem Description

Located along Interstate-90 between Bozeman, Montana and Livingston, Montana, Bozeman Pass faces challenges in providing safe travel for motorists (see Figure 1). During winter months, Bozeman Pass often experiences heavy snows and ice formation, conditions that are generally unpredictable and sudden. High winds present year-round concerns. Crash statistics from January 1995 to December 1998 show an average of approximately 137 total crashes per year through this corridor with up to 68 percent having weather or weather-related pavement conditions as a contributing factor (see Figure 2).

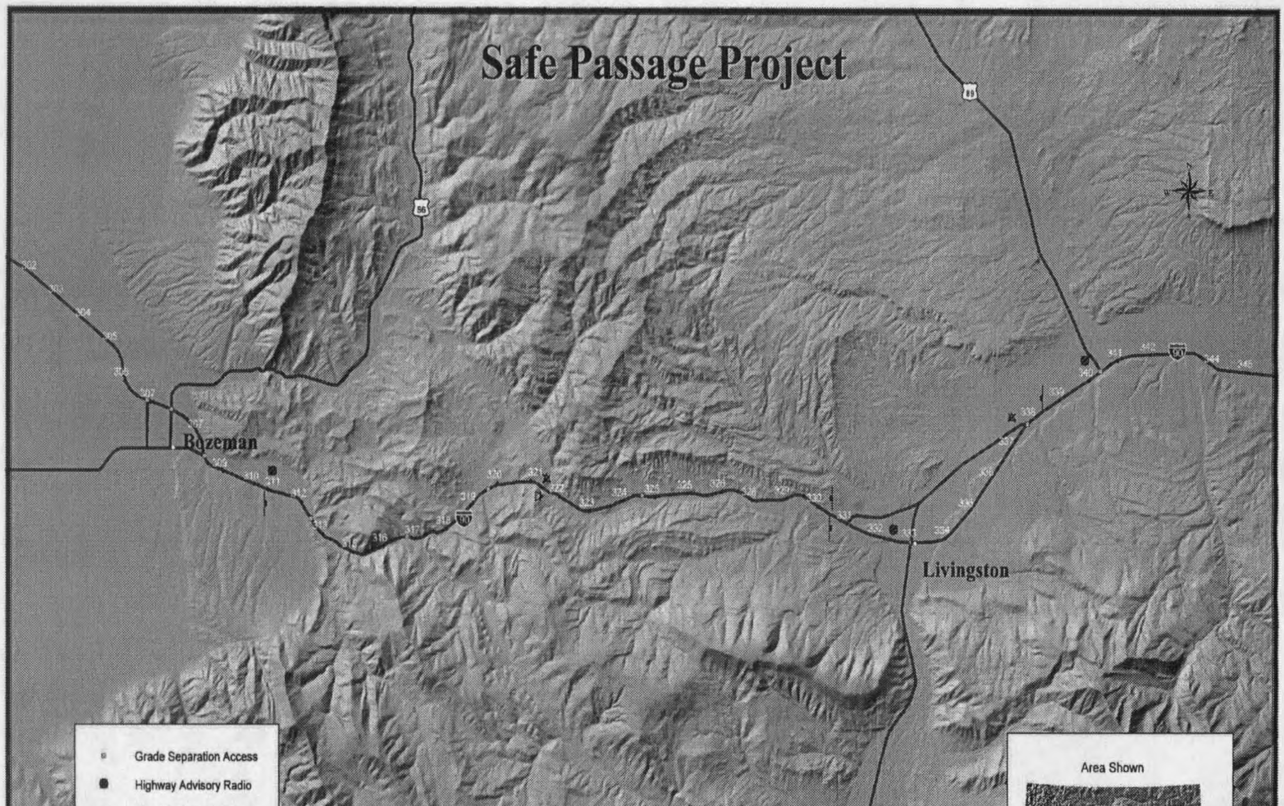

Figure 1. SAFE-PASSAGE Project Corridor.

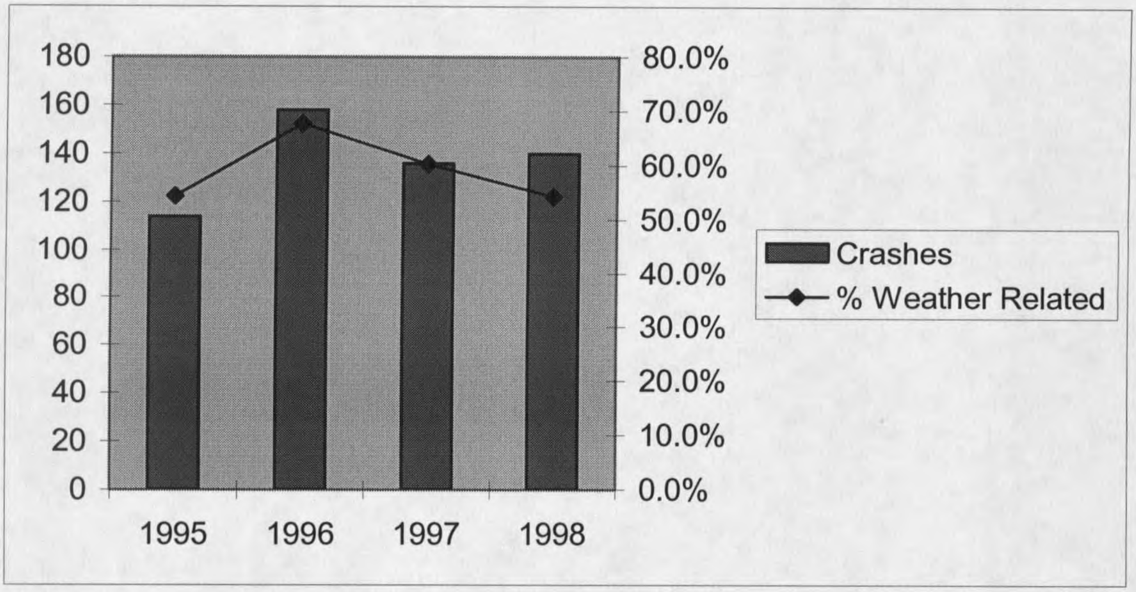

Figure 2. Bozeman Pass Corridor Crash History (16).

Weather has also been identified as one of the three single largest contributors to large truck crashes. These crashes have resulted in approximately 10 full interstate closures per year (2,3).

Multiple agencies, including transportation agencies, sheriff departments, police departments, fire departments, and other emergency response agencies at the state, county and local levels must be coordinated during adverse weather conditions or in the event of a resultant crash. Historically, response actions during or preceding adverse weather conditions (i.e., dispatching sand trucks or closing the roadway) have been subjectively guided by personal experience and judgement without a clear understanding of the factors or magnitude of factors that affect public safety. These action-based decisions can vary significantly from employee to employee depending on years of experience and inherent caution. With multiple agency involvement, the potential for inconsistent or ineffective actions is heightened.

The intent of this investigation is to minimize this subjectivity in decision-making by developing action guidelines on the basis of statistically confirmed presence and magnitude of various roadway and environmental conditions likely to result in the lowest level of safety. Crash severity, categorized as fatality, injury and property damage only, will be used as a surrogate indicator of level of safety.

In making this confirmation, the theoretical basis for this investigation is uncovered. Debate exists over the most appropriate statistical method for relating various risk factors to crash severity. Crash severity data has most often been modeled as discrete, unordered data using multinomial logistic (logit) regression. Some argue that crash severity data in fact represents ordered data with a fatality crash being more severe than an injury crash which in turn is more severe than a property damage only crash. For ordered data, ordered probability (ordered probit) models are most appropriate. The legitimacy of this debate will be examined as part of this investigation as well.

Background

This investigation is an integral component in a larger overall effort, the SAFE-PASSAGE Project. The SAFE-PASSAGE Project is a cooperative effort by Montana State University-Bozeman (MSU), the Western Transportation Institute (WTI), and the Montana Department of Transportation (MDT) with funding provided by the Research and Special Programs Administration (RSPA) of the U.S. Department of Transportation (USDOT).

The goals of the SAFE-PASSAGE Project are to optimize motorist safety and travel efficiency on Interstate-90 over Bozeman Pass and to provide a model for future developments in similar areas. In accomplishing these goals, three primary activities will occur:

- a computer model capable of forecasting pavement temperatures and roadway conditions will be implemented and validated,
- electronic Variable Message Signs (VMS) and improved Highway Advisory Radio (HAR) will be implemented and utilized to provide real-time motorist information, and
- a Rural Traffic Management Center (RTMC), effectively and efficiently coordinating and disseminating relevant information to all responsible agencies and to the motoring public, will be established.

This investigation will most directly benefit the third of these activities.

Bozeman Pass experiences an Average Annual Daily Traffic (AADT) of approximately 10,000 vehicles per day within the 30-mile corridor for over 100-million vehicle-miles of travel each year (see Figure 3). Traffic composition consists of approximately 20 percent commercial vehicles and recreation vehicles (see Figure 4) (4). Many motorists are from out-of-state and are therefore, unfamiliar with roadway alignment and weather effects.

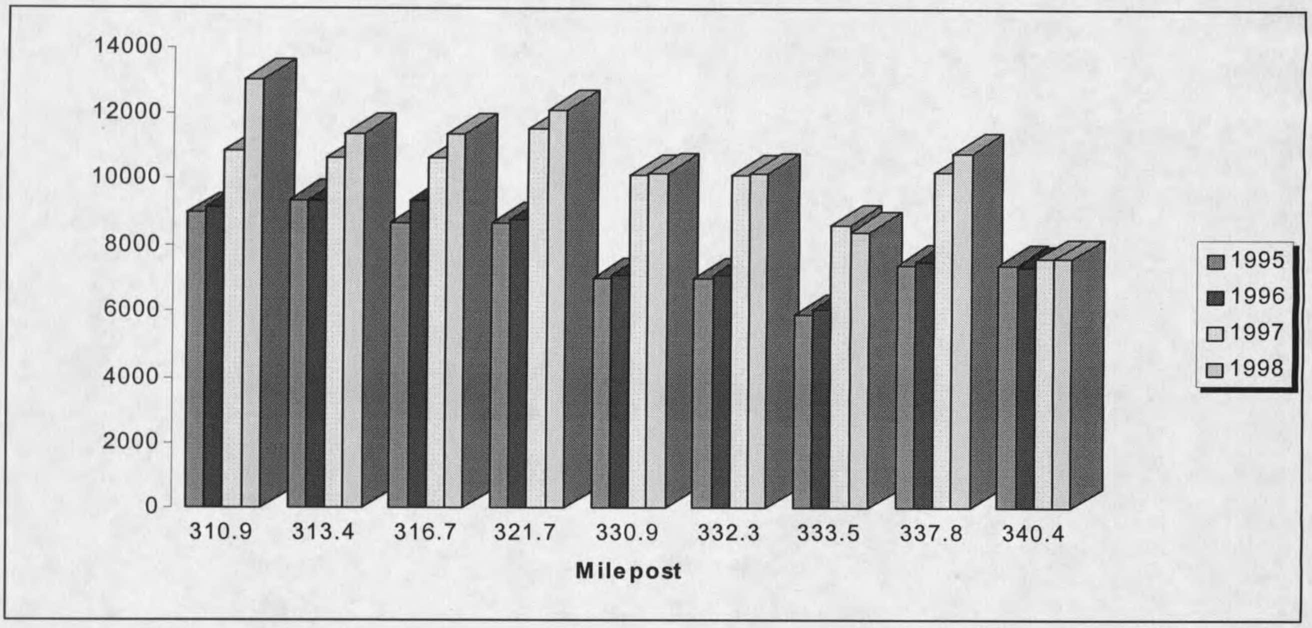

Figure 3. Bozeman Pass Corridor Average Annual Daily Traffic (3).

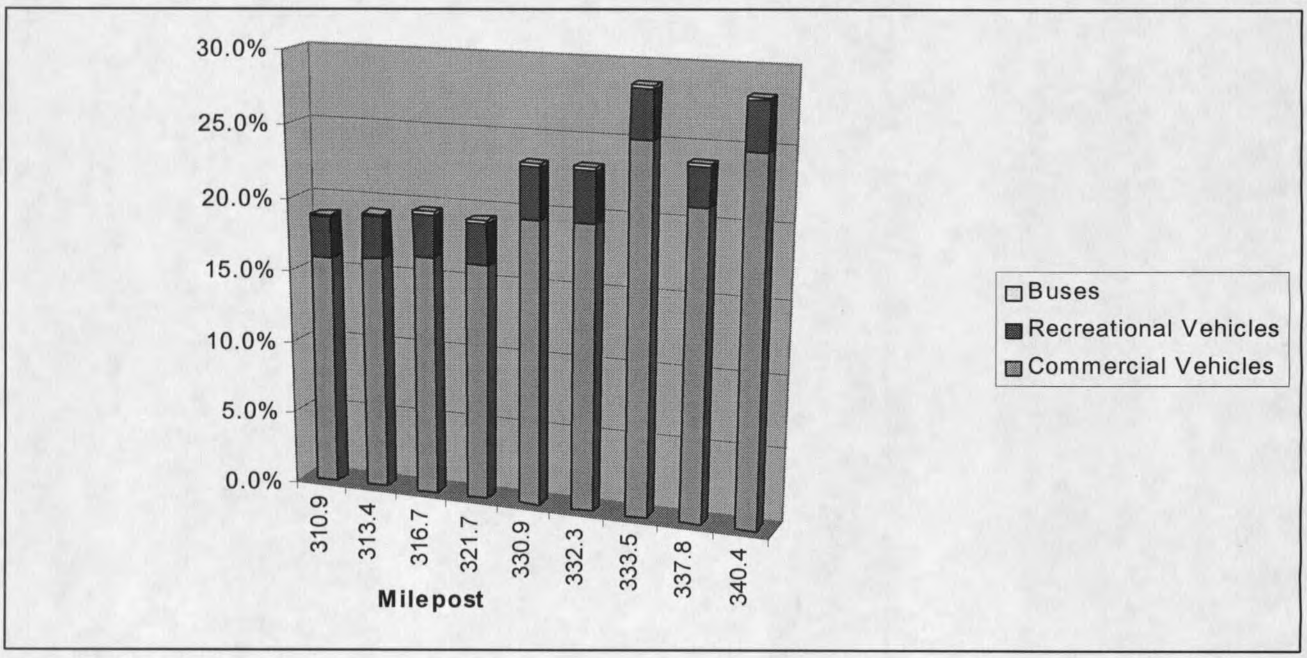

Figure 4. Bozeman Pass Corridor Traffic Stream Composition (3).

Report Purpose and Contents

The findings contained in this report respond to the twofold problem described previously and summarized here.

(1) Action-based decision-making related to adverse weather conditions by response personnel has been subjective in the past. Development of a statistical model relating weather and roadway conditions to crash severity would aid response personnel by defining predetermined courses of action dependent on those weather and roadway conditions deemed to result in the lowest levels of safety (5).

(2) Debate over the appropriate statistical form for modeling crash severity exists. By modeling severity data with both multinomial logit and ordered probit methods, a direct comparison will allow the most appropriate model form for this application to be determined.

This investigation provides additional insight in to the relationship between crash severity and risk factors with special emphasis on weather-related factors prevalent in mountainous areas. This report will support future efforts related to crash modeling in other corridors where safety and weather-related roadway conditions are also of primary concern.

Following this introductory material, Chapter 2 examines literature related to (1) previous modeling attempts for crash severity with additional focus on the model forms used, and (2) studies on the effect of weather-related roadway conditions on crash frequency and severity. Chapter 3 describes the methodology followed as part of this investigation including (1) data collection, assimilation and analysis, (2) descriptive statistics, (3) crash severity model development including model selection considerations and (4) model application for guiding response actions. Chapter 4 provides general descriptive statistics of the crashes in the Bozeman Pass Corridor for the years 1994 through 1999 followed by a description of the crash severity model results with the selection of the most appropriate model form and resulting response guidelines. This report concludes with a summary of findings and a series of suggested recommendations in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

This Chapter reviews literature on topics of significance to this investigation, including (1) previous efforts to identify the risk factors contributing to crash severity, (2) previous efforts to associate specific weather conditions with increasing crash risk and severity, and (3) existing policies regarding adverse weather related roadway maintenance and closure activities, as adopted by the Montana Department of Transportation. Findings from the literature are detailed below.

Risk Factors and Crash Severity

Previous efforts to identify various risk factors related to crash severity have been diverse, both empirically and methodologically. An empirical review of the available literature revealed (1) the primary focus of previous studies, (2) any factors considered possible contributors to crash severity, and (3) other significant findings. A methodological review of the available literature identified the variety of statistical approaches used to confirm contributing risk factors.

Empirical Review

Whereas this effort was limited to a well-defined interstate highway corridor for a specified period of time, previous efforts to determine crash severity risk factors have also been limited in their scope, focusing primarily on:

- specific crash severity types (i.e., fatalities),
- driver characteristics,
- vehicle types, and
- crash characteristics.

Table 1 summarizes this recent body of literature.

Table 1. Empirical Summary of Previous Crash Severity Literature.

Crash Severity and Severity Type		
Shibata and Fukuda	Risk Factors of Fatality in Motor Vehicle Traffic Accidents	1994
Crash Severity and Driver Characteristics		
Mercer	Influences On Passenger Vehicle Casualty Accident Frequency and Severity: Unemployment, Driver Gender, Driver Age, Drinking Driving and Restraint Device Use	1987
Levy	Youth and Traffic Safety: The Effects of Driving Age, Experience, and Education	1990
Lloyd	Alcohol and Fatal Road Accidents: Estimates of Risk in Australia 1983	1992
Holubowycz, Kloeden and McLean	Age, Sex and Blood Alcohol Concentration of Killed and Injured Drivers, Riders, and Passengers	1994
Kim, Nitz, Richardson and Li	Personal and Behavioral Predictors of Automobile Crash and Injury Severity	1995
Khattack, Pawlovich and Souleyrette	An Investigation of Injury Severity of Older Drivers in Iowa	2000

Table 1. Empirical Summary of Previous Crash Severity Literature (Continued).

Crash Severity and Vehicle Type		
Chirachavala, Cleveland and Kostyniuk	Severity of Large-Truck and Combination-Vehicle Accidents in Over-the-Road Service: A Discrete Multivariate Analysis	1984
Golob, Recker and Leonard	An Analysis of the Severity and Incident Duration of Truck Involved Freeway Accidents	1987
Shao	Estimating Car Driver Injury Severity In Car/Tractor-Trailer Collisions	1987
Alassar	Analysis of Heavy Truck Accident Severity	1988
Chang and Mannering	Analysis of Vehicle Occupancy and the Severity of Truck- and Non-Truck-Involved Accidents	1998
Duncan, Khattak and Council	Applying the Ordered Probit Model to Injury Severity in Truck-Passenger Car Rear-End Collisions	1998
Shankar and Mannering	An Exploratory Multinomial Logit Analysis of Single-Vehicle Motorcycle Accident Severity	1996
Chen and Jovanis	A Method Identifying Contributing Factors for Driver Injury Severity in Traffic Crashes	2000
Crash Severity and Crash Characteristics		
Good, Fox and Joubert	An In-depth Study of Accidents Involving Collisions With Utility Poles	1987
Jones and Whitfield	Predicting Injury Risk with "New Car Assessment Program" Crashworthiness Ratings	1988
Lui, McGee, Rhodes and Pollock	An Application of a Conditional Logistic Regression to Study the Effects of Safety Belts, Principle Impact Points, and Car Weights on Driver's Fatalities	1988
Malliaris, DeBlois and Digges	Light Vehicle Occupant Ejections – A Comprehensive Investigation	1996

Severity Type. One would expect the most frequent severity type analyzed in previous literature to be fatality crashes due to their higher overall cost and societal implications. *Shabata and Fukuda (1994)* focused entirely on fatality crashes and the potential effects of risk factors such as driving without a license, alcohol use, speed, and seatbelt and helmet use for all crashes within Fukuoka Prefecture in Japan in 1990. The most significant factor found to increase the likelihood of a fatality was motor vehicle speed. *Shabata and Fukuda* also found alcohol use significantly increased the likelihood of a fatality while seat belt use for cars and helmet use for motorcyclists significantly reduced the likelihood of a fatality (6).

Driver Characteristics. Many risk factors have been previously considered as contributors to crash severity. The majority of studies, however, focused on alcohol/drug use, restraint device use (i.e., seat belts) and other driver characteristics (i.e., age, gender and experience), which have long been popular in attempting to understand the most at-risk behaviors and groups involved in crashes (7, 8, 9, 10, 11, 12).

A study conducted in the mid-eighties by *Mercer (1987)* sought to identify the effects of unemployment, driver gender and age, restraint device use and drinking and driving on the frequency and severity of crashes over an 7-year span from January 1978 to December 1984 throughout British Columbia, Canada. *Mercer* used aggregate monthly rates for unemployment along with involvement rates of alcohol use, lack of restraint device use, age groups and gender to explain the effect of demographic shifts in the composition of the traffic stream on crash severity. It was assumed an increase in unemployment would take more young male drivers out of the traffic stream. *Mercer* found that changes in the demographic composition (i.e., age and gender) brought on by increased unemployment were more significantly related to crash severity than either alcohol use or restraint device use and should be considered in future studies analyzing crash severity and various risk factors (7).

Two studies by *Lloyd (1992)* and *Holubowycz, Kloeden and McLean (1994)* concentrated more on the solitary element of alcohol consumption and its effect on crash severity. Both studies attempted to isolate the effects of alcohol consumption on crash severity by simultaneously considering other potentially confounding factors such as driver age and gender and by limiting temporal and vehicle characteristics in the case of *Holubowycz, Kloeden and McLean*. Not surprisingly, both studies revealed an increase in Blood Alcohol Concentration (BAC, a measure of the amount of alcohol consumed) also increased the likelihood of a more severe or fatal crash. *Holubowycz, Kloeden and McLean* went farther; linking higher alcohol consumption to young and male drivers and consequently more severe crashes. Conversely, groups consuming less alcohol, older drivers and females, were less likely to be involved in a more severe crash. However, older drivers were identified to have a higher involvement in fatal crashes overall than their presence in the traffic stream suggested indicating an increased risk of dying in a crash with increasing age (8, 9).

Another study by *Kim et al. (1995)* focused on the relationship between alcohol use and crash severity but also introduced seatbelt use as a primary consideration. Again, alcohol use was found to significantly increase the likelihood of more severe crashes. The lack of seatbelt use also significantly increased the likelihood of more severe crashes. Though conclusive in its findings related to alcohol and seatbelt use, the study recommended further research into the effects of age on crash severity (10).

Levy (1990) investigated the relationship between crash severity and driver age, experience and education for only young drivers between the ages of 15 and 17 for all relevant crashes in 47 states for the years, 1976 to 1984. Findings of this study revealed the risk of a more severe crash increased as the age of the driver decreased. Recommendations from this finding supported an increase in the legal driving age rather than mandating driver's education, which was found to have a less significant effect on the severity of crashes. A second related study by *Khattak, Pawlovich and Souleyrette (2000)* focused on contributing factors to crash severity of older drivers in Iowa. Crash data from 1990 to 1997 for drivers over 65 years of age was used. Findings revealed among older drivers, the probability of a more severe crash increased as age increased and safety belts were not used. *Khattak, Pawlovich and Souleyrette* found the fatal involvement rate was nine times higher for drivers over 70 than for drivers aged 25 to 69 years. Additional factors found to significantly increase the severity of crashes with older drivers included crashes where: (1) the vehicle overturned or struck a fixed object, (2) a farm-related vehicle was involved and (3) the occurrence was on a rural road (11, 12).

Though varied and diverse in both focus and approach, the body of literature considering the effect of driver characteristics on crash severity revealed many common findings. Crash severity is likely to increase:

- with alcohol use,
- when seatbelts are not used,

- with younger aged drivers though among older drivers, the chance of fatality or more severe injuries increases with age, and
- with male drivers though, if involved, females are more likely to be more seriously injured than males.

While these factors have been studied singularly, they are more commonly studied in combination with other types of factors such as vehicle involvement or crash type.

Vehicle Type. Many efforts to identify factors contributing to crash severity have focused on vehicle type. Of these previous studies, the majority are devoted to crashes involving large trucks and combination vehicles (1, 13, 14, 15, 16, 17). A minority of previous studies consider crashes involving other vehicle types such as motorcycles (18) and buses (19).

The disproportionate amount of attention to large trucks and combination vehicles can be readily explained. "Large trucks have many unique operating characteristics such as high gross weight, long vehicle length and poor stopping distance, which have an impact on crash severity (1)." The primary focus in previous truck and combination vehicle crash investigations has been vehicle configuration, the type of collisions taking place and specifically, collisions between trucks and passenger cars.

A study by *Chirachavala, Cleveland and Kostyniuk (1984)* focused on the configuration of large trucks and combination vehicles to determine its influence on crash severity. The configuration types analyzed in this study included straight trucks, van semi-trailers, flatbed or tanker semi-trailers and doubles. For each configuration type, statistical models were estimated using a pool of independent main factors and their interactions, which included crash, vehicle, operation, driver, road and environmental characteristics. Results of these statistical models for each configuration type revealed crash type, road class, environmental conditions and various interactions between these three variables were the most frequent and significant factors in assessing the severity of crashes. Additionally, load status was found to be somewhat significant while driver characteristics, such as age, experience, hours of driving before the crash and scheduled driving time and time-of-day, were not significant. Regarding collision type, passenger car involvement resulted in the most severe crashes, followed by collisions with other commercial vehicles and single-vehicle crashes, respectively. Of the configuration types reviewed double trailer configurations, newly permitted at the time of the study, were found to result in the most severe crashes (13).

Golob, Recker and Leonard (1987) focused on the relationship between collision type and crash severity for large truck and passenger car involvement. *Golob, Recker and Leonard* analyzed truck-involved crashes from 1983 to 1984 on freeways in the Los Angeles, California area. Hit-object and rear-end were found to be the collision types most likely to result in a fatality, while overturns and broadside collisions were most likely to result in an injury crash. A number of supporting factors including the use of alcohol and driver errors, speeding, failure to yield and improper turns, were included in the analysis to identify the most significant causal factor leading to the collision types identified. Consistent with earlier findings, alcohol was found to be the primary causal factor for all collisions (14).

A second study, by *Duncan, Khattak and Council (1998)*, focused entirely on truck-passenger car crashes involving only rear-end collisions. *Duncan, Khattak and Council* considered a wide array of potentially significant factors affecting crash severity. Factors found to increase the chance of a more severe injury included darkness, high speed differentials, high speed limits, grades (especially when wet), being in a car struck by a truck rather than in a car striking a truck, driving under the influence of alcohol and being female. Factors found to decrease the chance of a more severe injury included snowy or icy roads, congestion, being in a station wagon and using a child restraint. Countermeasures recommended by *Duncan, Khattak and Council* included designing flatter grades, educating motorists as to the variation in truck speed on steep grades and lower speed limits on roads with high truck volumes (15).

Shao (1987), *Alassar (1988)*, and *Chang and Mannering (1998)* each continued efforts to identify the factors related to truck-passenger car crash severity by considering a much wider set of potential contributing factors than those investigated by either *Golob, Recker and Leonard* or *Duncan, Khattak and Council.*

Shao utilized crash records involving passenger cars and tractor-trailers on routes with higher levels of tractor-trailer travel in Maryland from 1983 and 1984. *Shao* was able to consider thirty-five individual variables for the nearly 1,700 compiled crash records. The individual variables were condensed into general categories, which included car driver characteristics, car and driver condition (before crash), truck driver characteristics, truck and driver condition (before crash), road condition and locality factor, traffic control, vehicular point of impact, cause of car/tractor-trailer collision, safety equipment usage in both vehicles (i.e., seatbelt), weather, road lighting conditions and post crash events. *Shao* indicated the most significant contributing factor to be car driver condition, illumination, truck driver condition, car point of impact, primary cause and weather. Specifically, the most significant individual factors identified included alcohol use by the car driver; lighting conditions of dawn, dusk or after dark; and high speed, failure of driver to stay in lane and yield properly and rear-end collisions (16).

A similar study was conducted by *Alassar* but concentrated more on the truck-related aspects of crashes rather than introducing car-related factors like *Shao*. *Alassar* primarily considered crash type, trip type, driver age, district, road class, environmental conditions and trailer body type but also investigated all possible two-way interactions of these variables to gain a better understanding of their effects on crash severity in combination. *Alassar* revealed truck collisions with any smaller mass as the most significant factor in increasing the odds of a crash fatality or injury. *Alassar* also noted minimal difference between crash severity odds for different sizes of large trucks. The conclusion formed from these two findings was beyond a critical size of a large truck, the severity of collisions between large trucks and passenger cars did not increase significantly. Alassar therefore recommended efforts be directed toward reducing the frequency of car-truck crashes rather than on reducing their severity. When a crash took place on a rural road, at night and with dry pavement conditions, linked with higher impact speeds, increased crash severity was noted. In agreement, when a crash involved collision with a fixed object, took place on an urban road or with wet or icy pavements, linked with slower impact speeds, the odds of a more severe injury or fatality significantly decreased (17).

Yet another effort to define relationships between risk factors and severity of truck-involved and non-truck-involved crashes was competed by *Chang and Mannering*. *Chang and Mannering* defined the relationship between vehicle occupancy and crash severity under the assumption that the more people involved in a crash, the higher the chances of a more serious injury or fatality. Data used in the study was collected from records of all reported crashes in the Seattle, Washington metropolitan area for a single year, 1994. A database of over 17,000 vehicles involved in crashes was used for analysis and included information on a wide array of possible factors, including roadway, temporal, environmental, driver, vehicle and crash characteristics. Findings of the study showed the difference in crash severity likelihoods between truck-involved and non-truck-involved crashes are most significantly reflected by crash characteristics variables. Factors found to increase severity for truck-involved crashes included high speed limits, vehicles making right or left turns and rear-end type collisions. The severity of crashes was significantly increased when trucks were involved and if vehicles had multiple occupants rather than single occupants, confirming the initial hypothesis of the study (1).

Again, though differences existed in both focus and approach, factors found to significantly increase the severity of crashes involving large trucks included:

- a large ratio between involved vehicles regarding size and weight,
- high impact speeds, and
- rear-end collisions.

Factors significantly decreasing the severity of crashes involving large trucks can be generalized as those which result in lowering vehicle speeds such as poor environmental conditions, urban roadway characteristics and fixed-object collisions.

Turning attention away from large truck-involved crashes, *Shankar and Mannering (1996)* considered motorcycle-involved crashes. Using five years of crash data from Washington State involving motorcycles, *Shankar and Mannering* advanced the more common univariate analysis of crash severity risk factors, typically devoted to helmet use, to a multivariate analysis considering a much wider array of potentially significant factors. The methodological difference between multivariate and univariate analysis is described later in this chapter. *Shankar and Mannering* uncovered important relationships between crash severity and motorcycle displacement, rider age, alcohol impaired riding, rider ejection, speed, rider attention, pavement surface condition and the type of road for single vehicle motorcycle involvements (18).

A second study by *Chen and Jovanis (2000)* identified significant factors, from a set of 39 possible influences and their interactions, influencing bus involved crash severity. *Chen and Jovanis* concluded the severity of injury to bus drivers increased when crashes occurred late at night or early in the morning, the bus driver was at fault, the collision was rear-end type or involved a large truck or tractor-trailer (19).

Crash Characteristics. Crash characteristics cover the broad range of factors possibly having an effect on the cause or resulting severity of a crash. Other classifications used include roadway characteristics (i.e., roadway geometric alignment conditions), traffic characteristics (i.e., traffic volume and vehicle type distribution conditions), and weather characteristics (i.e., precipitation, wind speed and visibility conditions). For the most part the elements discussed in the above literature reviewed (i.e., severity type, driver characteristics and vehicle type) can be classified as crash characteristics. Some specific elements, which can be included in efforts to determine the effects of various crash characteristics but were not summarized directly above, include the number of vehicles involved, the temporal conditions and the involvement of animals. These elements, along with most of the elements summarized above, will be evaluated through this effort.

Other efforts related to crash characteristics have been completed but are not directly applicable to this effort. The elements featured were not among those typically included in crash records. These efforts have included studies by *Good, Fox and Joubert (1987)* on vehicle/utility pole crashes, and *Malliaris, DeBlois and Digges (1988)* on crashes resulting in occupant ejection from the vehicle (20, 21). Two other studies were reviewed which analyzed the relationship between crash impact points and crash severity. Both *Jones and Whitfield (1988)* and *Lui et al. (1988)* linked findings from new car crash tests to real world crash data (22, 23).

Through this review of driver, vehicle and crash characteristics and their effects on crash severity, exclusion of key factors as part of this investigation has been avoided to the extent possible. Further, insight may be gained in comparatively examining the magnitude and direction of influence on crash severity found in this investigation as compared to previous efforts.

Methodological Review

The following section summarizes the methodological processes used in previous efforts to determine the significance of factors affecting crash severity. A variety of statistical methods have been applied in the investigation of crash severity, including univariate and multivariate methods and various forms of regression. A summary of the studies reviewed categorized by their statistical methodology is provided in Table 2.

Statistical methods are categorized as either univariate or multivariate based on the number of factors considered simultaneously. Univariate methods allow for the consideration of only one variable's effect on crash severity. Multivariate statistical techniques allow for the consideration of multiple factor effects on crash severity.

Univariate statistical techniques used in previous studies include hypothesis testing using the mean and variance of specific factors, correlation analysis and cross-tabulation methods. Hypothesis testing using the mean and variance was used by *Malliaris, DeBlois and Digges* to test for significant differences among crash severity levels, focusing on the impact of light vehicle occupant ejections (21). Correlation analysis was used by *Mercer* to analyze variables such as alcohol and restraint device use to determine the individual effects of each on crash severity (7). Correlation is a measure of how dependent one variable may be on another; the higher the correlation coefficient between two variables, the greater the dependency between variables. Cross-tabulation methods were used by *Holubowycz, Kloeden and McLean* to determine the relationship between various age and gender categories and blood alcohol concentration (BAC) and crash severity levels.

Table 2. Statistical Methods in Previous Crash Severity Investigations.

Univariate Methods		
Malliaris, DeBlois and Digges	Light Vehicle Occupant Ejections – A Comprehensive Investigation	1996
Mercer	Influences On Passenger Vehicle Casualty Accident Frequency and Severity: Unemployment, Driver Gender, Driver Age, Drinking Driving and Restraint Device Use	1987
Holubowycz, Kloeden and McLean	Age, Sex and Blood Alcohol Concentration of Killed and Injured Drivers, Riders, and Passengers	1994
Multivariate Methods		
Shao	Estimating Car Driver Injury Severity In Car/Tractor-Trailer Collisions	1987
Evans	Double Pair Comparison – A New Method to Determine How Occupant Characteristics Affect Fatality Risk in Traffic Crashes	1986
Lassarre	The Introduction of the Variable "Traffic Volume," "Speed" and "Belt-Wearing" Into A Predictive Model of the Severity of Accidents	1986
Fridstrom and Ingebrigtsen	An Aggregate Accident Model Based On Pooled, Regional Time-Series Data	1991
Log-linear Regression		
Golob, Recker and Leonard	An Analysis of the Severity and Incident Duration of Truck Involved Freeway Accidents	1987
Alassar	Analysis of Heavy Truck Accident Severity	1988
Levy	Youth and Traffic Safety: The Effects of Driving Age, Experience, and Education	1990
Kim, Nitz, Richardson and Li	Personal and Behavioral Predictors of Automobile Crash and Injury Severity	1995
Chen and Jovanis	A Method Identifying Contributing Factors for Driver Injury Severity in Traffic Crashes	2000

Table 2. Statistical Methods in Previous Crash Severity Investigations (Continued).

Ordered Probit Regression		
Duncan, Khattak and Council	Applying the Ordered Probit Model to Injury Severity in Truck-Passenger Car Rear-End Collisions	1998
Khattack, Pawlovich and Souleyrette	An Investigation of Injury Severity of Older Drivers in Iowa	2000
Logit Regression		
Chirachavala, Cleveland and Kostyniuk	Severity of Large-Truck and Combination-Vehicle Accidents in Over-the-Road Service: A Discrete Multivariate Analysis	1984
Jones and Whitfield	Predicting Injury Risk with "New Car Assessment Program" Crashworthiness Ratings	1988
Lui, McGee, Rhodes and Pollock	An Application of a Conditional Logistic Regression to Study the Effects of Safety Belts, Principle Impact Points, and Car Weights on Driver's Fatalities	1988
Shibata and Fukuda	Risk Factors of Fatality in Motor Vehicle Traffic Accidents	1994
Shankar and Mannering	An Exploratory Multinomial Logit Analysis of Single-Vehicle Motorcycle Accident Severity	1996
Shankar, Mannering and Barfield	Statistical Analysis of Accident Severity On Rural Freeways	1996
Chang and Mannering	Analysis of Vehicle Occupancy and the Severity of Truck- and Non-Truck-Involved Accidents	1998
Comparison of Alternate Methods		
O'Donnell and Connor	Predicting the Severity of Motor Vehicle Accident Injuries Using Models of Ordered Multiple Choice	1996

Holubowycz, Kloeden and McLean used the chi-square test and Student's t-test to confirm whether the noted differences were significantly different from that expected for the total population (9).

Though univariate statistical methods may offer more insight into the effects of a single variable, problems are introduced by their oversight of a multitude of potentially contributing factors and their interactions (18). Crash severity cannot be modeled accurately by a single variable.

To overcome the shortcomings of univariate methods, three multivariate techniques have been applied including a multivariate factor and discriminant analysis method used by *Shao*, a method of double-pair comparison used by *Evans (1986)* and time series analysis used by *Lassarre (1986)* and *Fridstrom and Ingerbrigtsen (1991)* (16, 24, 25, 26). Each of these methods appears is computationally intensive for determining the significance of an explanatory variable and the magnitude of its effect on crash severity.

The utility of the aforementioned investigations, using both univariate and multivariate, have been criticized because of their frequent use of aggregate data.

> "The disadvantage of using aggregate data is that it can result in a loss of information on the relationships between [crash] severity and contributing factors. The advantages of using disaggregate data not only include the capability of testing a broad range of factors that influence [crash] severity but also the capability of capturing powerful disaggregate information about how individual factors influence [crash] severity. Disaggregate analysis techniques theoretically can lead to more detailed and meaningful findings (1)."

One method, used more frequently than either univariate or multivariate methods, is the statistical method of log-linear modeling. Log-linear models have been used in studies by: (1) *Kim et al.* who focused on the effects of personal and behavioral factors, (2) *Levy* who focused on the effects of driver age, experience and education, (3) *Golob, Recker and Leonard* and *Alassar* to determine significant effects for large truck crash severity, and (4) *Chen and Jovanis* who focused on the severity of crashes involving buses (10, 11, 14, 17, 19). Log-linear models incorporate tests of independence between variables and provide measures of the magnitude, direction and statistical significance of main effects and interactions. The generalized log-linear model as described by *Kim et al.*, seeks to explain cell frequencies using an additive model. A cell represents the frequency of occurrence at specified levels for each variable considered in the model. An example of a "saturated" log-linear model for a three-way frequency table with variables A, B and C follows:

$$\log_e(m_{ijk}) = u + u_{A(i)} + u_{B(j)} + u_{C(k)} + u_{AB(ij)} + u_{AC(ik)} + u_{BC(jk)} + u_{ABC(ijk)}$$

where m_{ijk} is the expected frequency of cell ijk, where i, j, and k represent the levels of variables A, B and C respectively. The model is referred to as "saturated" because it includes all possible main effects (i.e., $u_{A(i)}$, $u_{B(j)}$, $u_{C(k)}$) and interactions (i.e., $u_{AB(ij)}$, $u_{AC(ik)}$, $u_{BC(jk)}$, $u_{ABC(ijk)}$) (10).

Log-linear modeling has several disadvantages, which discourage its use in this effort. First, log-linear modeling is best suited to discrete data sets, not those that include continuous data elements (10). Second, it is not well suited to large data sets with many variables. The determination of variable significance is cumbersome requiring the computation of chi-square statistics to determine a primary level of significance followed by Cochran-Mantel-Haenszel tests to further determine the significance of prospective variables and interactions. If there is sparseness among variables in the data set, this process may become inadequate, necessitating further computations (19). Finally, the resulting estimated parameters from the log-linear model do not provide a direct measure of the effects of the independent variables and their interactions on the dependent variable, requiring the calculation of odds-ratios for each significant variable. If the resulting odds-ratio for a specific variable and crash severity level is greater than one, the more likely that severity of outcome is when the variable is present in a crash. If the odds-ratio is less than one, the less likely the severity outcome is in the result of a crash with the variable present (10).

After discounting the previously described statistical methods, two remaining methods show promise for analyzing crash severity: (1) the ordered probit regression model and (2) the logit regression model. Either model can analyze a variety of data elements in a less computationally intensive manner, produce results that are more accurate and less suspect to inherent bias by inclusion of more variables, and offer direct results that can be used to gauge a variable's effect on crash severity in relation to other variables.

Ordered probit regression is best-suited and most typically applied to situations investigating the effect of various independent variables on a discrete dependent variable. The discrete dependent variable must be ordered in nature. The modeling of crash severity is viewed by some as appropriate for ordered probit analysis methods. Crash severity is typically categorized by the most severe result of the crash such as fatality, incapacitating injury, non-incapacitating injury, no evident injury but with reports of pain and no injury. More often, the severity of a crash is generalized as fatal, injury or property-damage-only. A specific advantage in using ordered probit regression to model crash severity is the assumption of unequal differences between categories of the dependent variable. For example, the difference between a fatal crash and an injury crash is not the same as the difference between a property-damage-only crash and an injury crash. This captures the qualitative differences between crash severity levels (15).

Khattak, Pawlovich and Souleyrette, Duncan Khattak and Council, and O'Donnell and Connor (1996) each utilized ordered probit regression to analyze crash severity. As discussed in the above empirical review of these efforts, *Khattak, Pawlovich and Souleyrette* focused on the factors affecting the severity of crashes involving older drivers while *Duncan Khattak and Council* focused on the factors affecting the severity of truck-passenger car crashes involving rear-end collisions (12, 15, 27).

O'Donnell and Connor attempted to model the factors affecting the severity of involving cars in New South Wales, Australia, from 1991, using both ordered probit and logit, specifically ordered logit, regression techniques. The primary difference between these two models is the difference in assumptions related to their error terms. The ordered probit model is assumed to have normally distributed error terms while the error terms for the ordered logit model are assumed to be independent and have a generalized extreme value distribution (28). *O'Donnell and Connor* revealed comparable results from the ordered logit and probit model estimates with respect to both magnitude and direction of influence for all variables except for time of crash. However, the estimated coefficients for the probit model were always lower than that of the logit model, leading to the conclusion that predicted severity would always be less for the ordered probit than for the logit model. The effort by *O'Donnell and Connor* was the only investigation found to utilize the ordered logit method (27).

Conversely, the standard binomial logit regression model has been utilized frequently to investigate crash severity (i.e., *Chirachavala, Cleveland and Kostnyiuk, Jones and Whitfield* and *Lui et al.*) (13, 22, 23). Despite its frequent application, a noted shortcoming in the use of the binomial logit model is its ability to compare between only two levels of alternatives for the chosen dependent variable. In the case of crash severity, severity levels would be redefined to two categories such as fatal or non-fatal. The binomial logit regression model can be represented as:

$$P_n(i) = \frac{e^{\beta X + \varepsilon}}{1 + e^{\beta X + \varepsilon}}$$

where

$P_n(i)$ represents the probability of a specific crash severity level (i.e., fatal, non-fatal)

β is a vector of regression parameters estimated by maximum likelihood methods

X is a vector of independent explanatory variables (i.e., pavement condition, driver age, etc.)

ε is a random error or disturbance term that accounts for unobserved effects (29).

To overcome the shortcomings of standard binomial logit regression, the multinomial logit model was used by *Shankar and Mannering* to analyze single-vehicle motorcycle crash severity (18).

The multinomial logit regression model is as follows:

$$P_n(i) = \frac{e^{\beta X_{in} + \varepsilon}}{\sum_I e^{\beta X_{In} + \varepsilon}}$$

where all variables are as previously defined. While multinomial logit regression better describes crash severity categories, *Shankar and Mannering* noted a problem related to the error term assumption of independence between severity levels. Shankar and Mannering understood that some severity types could share unobserved terms and have a correlation that violates the independence assumption, leading to the erroneous estimation of model coefficients. The problem of shared unobservables, referred to as an independence of irrelevant alternatives (IIA), can be accounted for through the Small-Hsiao test to verify insignificance at a specified confidence level.

In an effort to correct for inadequacy in the assumption of error terms for the multinomial logit model, a modified version, the nested logit model, was used in studies by *Shankar, Mannering and Barfield (1996)* and *Chang and Mannering* (1, 30). The nested logit model groups the possible correlated error terms into a "nest" by estimating a model that includes only individuals choosing the nested alternatives (28). Figure 5 provides a graphical example of the difference in structure between the standard multinomial and nested logit models. The nested logit model requires a more specific description of crash severity where correlation between the error terms for successive levels may be more apparent such as in Figure 5. Only three levels of crash severity (fatality, injury and property-damage-only) were available for this effort, therefore "nesting" of any two levels would in effect turn the nested logit model into the binomial logit model, which would provide less specific findings than multinomial logit regression.

A more complete description of both the ordered probit and multinomial logit models, detailing their differences and relevant assumptions, is provided in Chapter 3.

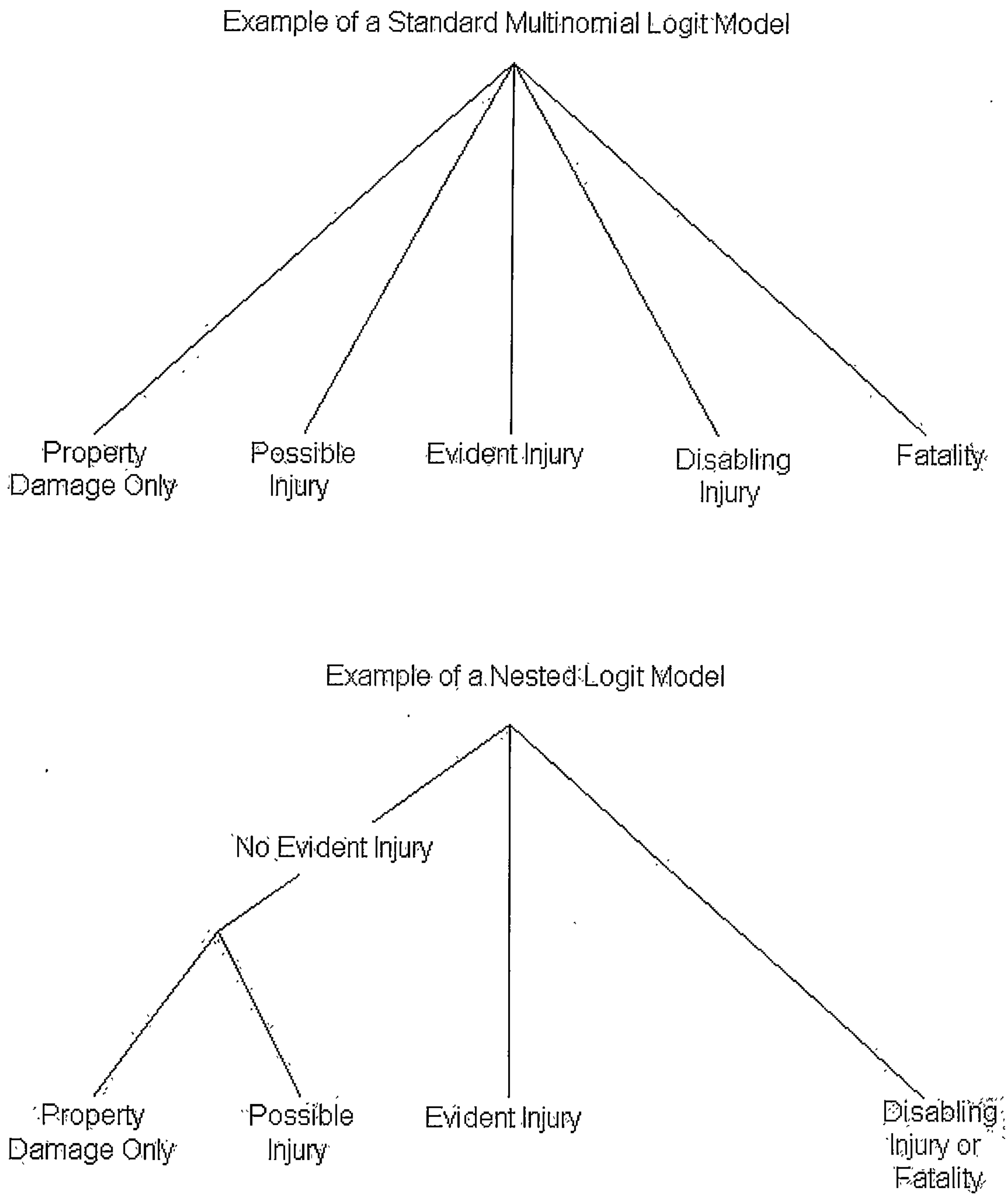

Figure 5. Standard Multinomial Logit and Nested Logit Model Structure (30).

Adverse Weather and Crash Risk and Severity

Many of the studies described previously explored the impacts of weather conditions on crash risk and severity. For the most part, these efforts did not focus extensively on the effects of weather, considering only general pavement conditions (i.e., icy, wet or dry) and atmospheric conditions (i.e., clear, foggy, raining or snowing) at the time of the crash.

Council, Khattak and Kantor (1998) did focus entirely on the role of adverse weather and its interactions with driver and roadway characteristics on the risk and severity of crashes. Specifically, *Council, Khattak and Kantor* used binary probit models to estimate crash risk and ordered probit models to analyze injury severity for crashes on limited-access roads in North Carolina from 1990 to 1995. The effort's motivation was to gain a clearer understanding of the implications of advanced weather systems on traffic safety.

Council, Khattak and Kantor estimated the likelihood of single-vehicle versus two-vehicle crashes, and, if two-vehicle crashes, the likelihood of rear-end versus sideswipe crashes. These crash types: (1) were assumed to be the most affected by adverse weather, (2) constituted the majority of crashes on limited-access highways and (3) aided in the formulation and testing of the hypothesis by providing a narrowed focus for the effort. Overall the study revealed adverse weather (i.e., fog, rain or snow) and resulting slippery road conditions (i.e., wet or icy/snowy) increased the risk of single-vehicle crashes relative to two-vehicle crashes. The risk of rear-end, two-vehicle crashes increased relative to sideswipes under the same conditions. These findings indicated drivers do not compensate fully for the lower visibility and more slippery road surfaces on the limited-access highways studied.

Council, Khattak and Kantor went on to analyze the effects of adverse weather, slippery road surfaces and other related direct variables and interactions on the severity of crashes. The study revealed that under the direct effect of adverse weather conditions and slippery road surfaces, the probability of more severe injuries and fatalities is reduced while the probability of minor-level injuries is increased. The reduction in fatality likelihoods under adverse weather conditions and slippery road surfaces was much lower than that for a severe-level injury in absolute terms. Additional findings revealed single-vehicle crashes resulted in a higher probability of more severe injuries or fatalities than the two-vehicle crash types reviewed (rear-ends and sideswipes).

Council, Khattak and Kantor qualified the effects of under-reported low-severity crashes, which may have biased the findings. Given this potential bias, the likelihood of single-vehicle crash occurrence may be conservative while the estimates of two-vehicle crash types and crash severity were most likely unaffected. Final conclusions suggested that while drivers in adverse weather conditions or on slippery road surfaces made some adjustment of behavior resulting in reduced speed, increased caution, and reduced crash severity, the adjustments were sufficient to refute a more frequent crash occurrence than under dry pavement surface conditions or clear weather (31).

The findings of *Council, Khattak and Kantor*, while providing substantial background on the effects of weather on crash risk and severity, should not be assumed to be directly transferable to this effort for two reasons. First only 26 percent of vehicle involvements reviewed occurred during adverse weather conditions, with 29 percent occurring on slippery pavement surfaces. Sixty-eight percent of crashes reviewed in the Safe Passage Corridor as part of this effort involved weather or weather-related pavement conditions. Second, the analysis by *Council, Khattak and Kantor* only considered general weather information (i.e., atmospheric conditions and pavement surface conditions) as reported by the responding police officer to the crash scene. This effort includes much more detailed weather conditions, such as precipitation rates, pavement surface temperature and wind speed, provided by road weather information systems.

Adverse Weather Response Policies

Recall that a primary objective of this effort is to reduce decision-making subjectivity through the development of response-related guidelines under adverse weather conditions. Before recommendations can be made, a review of the current weather response policies and procedures for the corridor was undertaken. This review included the *Winter Maintenance Standards Definitions* manual produced by the Montana Department of Transportation (MDT) and interviews of the MDT Maintenance Department personnel responsible for decision-making and response activities through most of the corridor.

Winter Maintenance Response Priorities

The *Winter Maintenance Standards Definitions* manual details the priorities for winter maintenance resource allocation on the basis of roadway classification. This prioritization scheme is used by Area Maintenance Chiefs to guide response activities during winter storm events. Priorities for plowing, sanding, and chemical anti-icing and deicing activities are summarized in Table 3.

The Area Maintenance Chiefs and/or District Administrators have the ability to set the desired level of service of a road other than what the guidelines indicate. Desired level of service mar be influenced by any of the following factors:

- safety,
- average daily traffic (ADT),
- commuter routes,
- availability of alternate routes,
- public interest and concern,
- potential economic impact,
- consequence of not providing a higher level of service and
- available resources.

Because MDT's snow and ice control operations have budget limitations on personnel, equipment and materials available, justification for the change must be provided as well as a description of the anticipated effects on the area's winter maintenance budget (32).

Table 3. MDT Winter Storm Response Priorities (32).

Roadway Type	Typical Coverage Time	Recommended Levels of Clearance
Level I Classification		
Urban (3-mile radius) routes with 5,000 or greater ADT	24 hours or until a bare pavement is achieved in the primary driving lane(s)	All lanes should have intermittently bare pavement before coverage time is reduced. This should be accomplished using an anti-icing program
Level I-A Classification		
Interstates or roadways with 3,000 or greater ADT	19 hours – 5:00 A.M. until 12:00 A.M. or until intermittently bare pavement exists in the primary driving lane(s)	The right lane on divided roadways and both lanes on two-lane roads should have bare wheel paths with intermittent bare pavement before coverage time is reduced
Level II Classification		
High volume roadways with ADTs greater than 1,000 but less than 3,000	17 hours – 5:00 A.M. until 10:00 P.M. or until snow packed and/or icy surfaces have been treated with abrasive, or abrasive/chemical combinations	Both lanes should have reasonable pavement surface with sanded hills, bridges, intersections and curves before coverage time is reduced
Level III Classification		
Low volume roadways with ADTs greater than 200 and less than 1,000	15 hours – 5:00 A.M. until 8:00 P.M. or as available personnel and equipment permit and until hills, curves, bridges and intersections have been deiced or sanded	A reasonable pavement surface each with intermittent sanded areas (hills, bridges, intersections and curves) should be attained before coverage time is reduced.
Level IV Classification		
Roadways with an ADT less than 200	8 hours or regularly scheduled work hours and only as personnel and equipment permit	Should provide a plowed roadway surface during regular scheduled work hours. Abrasives may be used on hills, bridges, curves and intersections.
Level V Classification		
Seasonal roadways	N/A	Those Roadways that receive no scheduled winter maintenance.

For this effort, the Safe Passage Corridor is classified as Level I-A or higher, meaning response to winter storm events anywhere along its length is of high priority to area maintenance personnel. The primary objective on these roads is to keep a minimum of one driving lane open in each direction throughout the duration of the storm. Plowing activities and application of sand and chemical anti-icing and deicing agents should be continued until intermittent bare pavement sections exist in the primary driving lane and the remaining driving lanes and shoulders are cleared. The exception would be only when blizzard and/or severe weather conditions exist that compromise the safety of maintenance personnel and/or the traveling public. Additionally, guidelines on application of anti-icing and deicing chemical agents indicate their use only prior to or after the storm event when acceptable weather conditions are present (32).

Winter Maintenance Response Procedures

As stated earlier, the decision-making process for winter and other adverse weather condition response procedures in the project corridor are subjective in nature. Responses are based on personal experience and judgment not on previously defined levels of environmental conditions. Decision-making authority rests with the Bozeman Area Maintenance Chief who usually acts on information and recommendations provided by plow operators or the Montana Highway Patrol. Typical decisions required by the Area Maintenance Chief or support staff include: (1) when to initiate winter maintenance activities, (2) what type(s) of activities to undertake (i.e., plowing, sanding and/or application of chemical deicer), (3) when to institute chain requirements for heavy vehicles, (4) when to close segments of the roadway in one or both directions and (5) where and when to stop these activities.

Response for winter maintenance initiates if weather forecasts call for snowfall or the Road Weather Information System (RWIS) stations report precipitation and a suitably cold pavement surface temperature. Typical initial response to the onset of precipitation includes the dispatch of two plows/sanders from the Bozeman maintenance yard plus additional response from the Livingston maintenance yard. In the Safe Passage Corridor, plows dispatched from Bozeman are responsible for the roadway between Rocky Canyon and Bozeman Hill (Milepost 310 to approximately Milepost 325) while Livingston plows maintain the road east of Bozeman Hill (approximately Milepost 325 to Milepost 340). Initial response can also include pre-treatment of bridge decks with chemical deicer to prevent precipitation from freezing on them before the rest of the roadway.

The rate at which plow operators work is based on their personal judgment of their ability to maintain the road to the level prescribed in the *Winter Maintenance Standards Definitions* manual. The operators vary their rates accordingly but may request additional plows if precipitation or drifting rates are preventing them from maintaining the road at the prescribed level.

Sanding of the road surface is completed in conjunction with plowing. The sand used consists of three to four percent salt to prevent freezing in the stockpiles. Chemical deicer is sometimes mixed into the sand, which allows enough ice melt for the sand to penetrate and increase traction. Chemical deicer is only applied, other than in pre-treatment of bridge decks, when suitable environmental conditions exist, such as include the cessation of precipitation, rising temperatures (between 20 and 30 degrees Fahrenheit), and forecasts which do not call for new precipitation. If new precipitation falls on chemical deicer or if conditions are cold enough, the treated ice surface will actually become slicker than the untreated ice surface.

The institution of chain requirements on heavy vehicles is typically made only after reports of plow operators or the Montana Highway Patrol indicate vehicles are having difficulty maneuvering. Personnel at the Bozeman Maintenance Office activate "Chains Required" signs electronically.

Although the Montana Highway Patrol has initiated road closure activities in the past, the decision to close the road is under the sole authority of MDT personnel (33). Once the decision to close the road has been made, one to two hours may actually elapse before complete closure is accomplished. Road closure requires the response of nearly all active maintenance personnel in the Bozeman Area to post signs and close gates on appropriate on-ramps and driving lanes. Road closures most often result from a crash with significant blockage or hazardous materials. Weather-related closures are much less frequent. The most frequent type of weather closure results from a lack of visibility (i.e., high winds and blowing snow) most often occurring just east of Livingston. Weather-related closures have also occurred because of slippery road surfaces. Weather-related closures are avoided as much as possible because the time to enact a road closure is usually longer than the time necessary to improve roadway conditions through plowing, sanding, deicing, etc.

As this section shows, the decision-making process, guiding winter maintenance activities performed within the Safe Passage Corridor, is highly subjective. The high priority for winter maintenance through the Safe Passage Corridor means this effort may not lead to significant changes in decision-making for initiation of activities. However, this effort may effect change in the decision-making processes for chain requirements and roadway closure, which are highly dependent on the personal opinions of plow operators and highway patrolmen traveling through the corridor.

CHAPTER 3

METHODOLOGY

Data collection procedures and modeling methodologies used to investigate and predict crash severity over Bozeman Pass are described in this Chapter. Specifically, this Chapter describes the methodologies related to: (1) data collection, assimilation and coding; (2) descriptive statistics, (3) severity model development and (4) model application in developing response guidelines.

Data Collection, Assimilation and Coding

Data to support the development of the crash severity model related to, (1) crashes, (2) roadway characteristics, (3) traffic characteristics, and (4) weather.

Crash Data

Data was obtained for all crashes occurring within the project corridor for a six-year span from January 1994 to December 1999. The Montana Department of Transportation's (MDT's) Safety Management Section provided the data in hard copy format requiring manual entry into an Excel spreadsheet. The crash-related data elements of interest included the following:

- crash severity;
- milepost and direction of travel;
- year, month, day of week and time of the day;
- location on roadway (i.e., shoulder, junction, etc.);
- traffic control in place (i.e., warning sign, pavement markings, etc.);
- road and light conditions;
- vehicle and/or trailer type and age;
- number of vehicles involved;
- collision type (i.e., sideswipe, rear-end);
- if an animal was involved;
- age and gender of driver; and
- if the driver was intoxicated.

Roadway Characteristic Data

The roadway characteristics (i.e., geometrics and roadside appurtenances) for the project corridor were then supplemented into the crash database, using milepost and direction of travel as the linking data elements. Roadway characteristics of interest included the following:

- lane widths;
- left and right shoulder widths;
- horizontal curve lengths, directions, radii, and superelevations;

- vertical curve lengths, direction, and roadway grade;
- presence of a spiral curve;
- presence of left and right guardrail;
- presence of bridges;
- presence of off and on ramps;
- presence of turnouts;
- presence of median turnarounds; and
- types of median treatments.

This data was obtained from several different sources. The first was the Montana Department of Transportation (MDT) Image Viewer, which has photos taken every ten meters along the roadway, with the location of the photos known to the one-thousandth of a milepost. The Image Viewer data was supplemented with data from MDT construction plans and MDT. Lastly, some minor field data collection was required to obtain the horizontal curve superelevation rates. This data was successfully collected using a ball bank indicator. The combination of these multiple sources provided for a comprehensive and detailed set of roadway-related data elements for the project corridor.

Traffic Characteristics

Traffic volume and classification data, including Average Annual Daily Traffic (AADT) volumes and the percentage of recreational vehicles, buses and commercial vehicles in the traffic stream, were supplemented next into the crash database. This data was obtained from the Montana Department of Transportation's Data and Statistics Bureau and was linked to the crash data using milepost, direction of travel and year. Additionally, speed limit data was collected to determine it possible effect as well since the speed limit through the corridor changed twice during the data collection period.

Weather Data

Detailed weather-related information obtained from the vicinity Road Weather Information Stations (RWIS) was used to complete the database. Weather data elements of interest included:

- surface temperature,
- air temperature,
- dewpoint,
- pavement surface status,
- precipitation,
- wind speed, and
- wind direction.

Historical weather records were linked to the crash data using milepost (to ensure nearest RWIS), date and time of day.

Before generating descriptive statistics and performing the modeling exercises, minor data transformations were necessary on some elements in the crash database. Data that had multiple non-numeric choices (i.e., collision type = rear end, head on, sideswipe, etc.)

were transformed into singular indicator variables. Continuous, numeric data, such as the average annual daily traffic, horizontal and vertical curve lengths or percent commercial vehicles in the traffic stream were used directly without transformation. Table 4 contains a list of all variables considered in this investigation.

Descriptive Statistics

Prior to developing the crash severity model, general descriptive statistics describing project corridor crash characteristics from January 1994 to December 1999, were examined. The descriptive statistics considered severity, collision type, temporal, environmental, location, vehicle and driver characteristics. Descriptive findings were expressed using histograms, continuous data plots, and pie charts to most clearly display the general trends of crashes within the corridor. National highway safety and crash statistics, obtained from the Fatal Accident Reporting System (FARS) database, were provided for comparative purposes to further the understanding of the safety challenges encountered in this corridor. Descriptive findings are detailed in Chapter 4.

Table 4. Data Elements.

Data Element	Code	Response
CRASH DATA		
Severity	1	Fatality
	2	Injury
	3	PDO
Milepost	Entered Directly	
Direction	0	West
	1	East
	2	South
	3	North
Year	94-99	1994 through 1999
Month	1 - 12	Jan. through Dec.
Day	1 – 7	Sun. through Sat.
Time	Converted to decimal, 0 - 24	
Road Location	1	On roadway
	2	Shoulder
	3	Median
	4	Outside-shoulder lt.
	5	Outside-shoulder rt.
	6	Off road-unknown
	7	Gore
	8	Unknown
Traffic Control	1	Traffic signal
	2	Stop sign
	3	Other reg. sign
	4	Warning sign
	5	Pavement marking
	6	None
	7	Other
Road Condition	1	Dry
	2	Wet
	3	Snow or slush
	4	Icy
	5	Sand, mud, dirt, oil
	6	Loose gravel
	7	Other
	8	Unknown
Light Condition	1	Daylight
	2	Dark – no lit
	3	Dark – lit
	4	Dawn
	5	Dusk
	6	Unknown

Data Element	Code	Response
CRASH DATA (CONT.)		
Vehicle Type	1	Motorcycle
	2	Passenger car
	3	Van/ SUV
	4	Pickup
	5	Large truck
	6	Other
	7	Unknown
Trailer Type	1	No trailer
	2	Utility trailer
	3	Semi trailer
	4	Full trailer
	5	2 trailers
	6	3 trailers
	7	Camping
	8	Other
Vehicle Year	Entered Directly	
No. of Vehicles	Entered Directly	
Collision Type	1	Rear end
	2	Sideswipe-same dir.
	3	Sideswipe-opp. dir.
	4	Right angle
	5	Head on
	6	Other
Animal-involved	0	Yes
	1	No
Gender	0	Female
	1	Male
Alcohol-involved	0	No
	1	Yes
ROADWAY DATA		
Lt-shoulder. Width	Entered Directly (ft)	
Rt-shoulder. Width	Entered Directly (ft)	
Lt-side Guardrail	0	Not Present
	1	Present
Rt-side Guardrail	0	Not Present
	1	Present
Median	0	Not Present
	1	Present
Hor. Curve Length.	Entered Directly (ft)	
Hor. Curve Radius	Entered Directly (ft)	
Hor. Curve Superelevation	Entered Directly	

Table 4. Data Elements (Continued).

ROADWAY DATA (CONT.)		
Horiz. Curve Dir.	0	No Curve
	1	Left
	2	Right
Spiral Curve	0	Not Present
	1	Present
Vert. Curve Length	Entered Directly (ft)	
Vert. Curve Dir.	0	No Curve
	1	Uphill
	2	Downhill
Vert. Curve Grade	Entered Directly	
Bridge	0	Not Present
	1	Present
Off-Ramp	0	Not Present
	1	Present
On-Ramp	0	Not Present
	1	Present
Turnout	0	Not Present
	1	Present
Median Turnabout	0	Not Present
	1	Present
TRAFFIC DATA		
AADT	Entered Directly	
% RVs	Entered Directly	
% Buses	Entered Directly	
% Com. Vehicles	Entered Directly	

TRAFFIC DATA (CONT.)		
Speed Limit	1	65 mph
	2	Basic Rule
	3	75/65 mph
WEATHER DATA		
Surface Temp.	Entered Directly (°F)	
Air Temp.	Entered Directly (°F)	
Dew Point	Entered Directly (°F)	
Precipitation	0	No
	1	Yes
Pave. Sfc. Status	1	Dry
	2	Damp
	3	Wet
	4	Chem. Wet
	5	Snow/Ice
Wind Direction	1	North
	2	North East
	3	East
	4	South East
	5	South
	6	South West
	7	West
	8	North West
Wind Speed	Entered Directly (mph)	

Model Development

Selection of the appropriate model form to describe crash severity is not straightforward. Crash severity is most often classified at the following three levels:

(1) fatality: a fatality of the driver and/or a passenger resulted from the crash,

(2) injury: any driver or passenger was injured to the point of requiring medical attention in the crash or

(3) property damage only: damage resulting from the crash was limited to the vehicles involved or nearby property.

The nature of the debate over the appropriate analytical method for modeling crash severity data centers on whether the data classification indicates an order of response (i.e., there is a progression in the rank of the severity of an crash in such a manner that a fatality crash is considered more severe than and injury crash which is in turn more severe than a property damage only crash).

Ordered Probit Regression

If one assumes a progression in rank in the above manner, the data set is classified as both ordered and discrete. The most appropriate model form used to create the statistical model would be an ordered probability (ordered probit) regression function (3). Ordered probit models define an unobserved variable, z, such that:

$$z = \beta X + \varepsilon$$

where

β is a vector of estimable regression parameters determined by maximum likelihood methods,

X is a vector of measurable factors (e.g., collision type, driver age, precipitation rate) that define ranking, and

ε is a random error term assumed to be normally distributed.

The ordered probit equation allows the determination of various threshold values that reflect the discrete nature of the data:

$y = 1$ if $z \leq \mu_0$

$y = 2$ if $\mu_0 < z \leq \mu_1$

$y = 3$ if $z \geq \mu_1$

where

y is the actual or observed severity level and

μ is an estimable parameter that defines y.

For this effort:

$y = 1$ represents the severity level fatality,

$y = 2$ represents the severity level injury, and

$y = 3$ represents the severity level property damage only.

Multinomial Logit Regression

Though intuitive that some inherent order exists in crash severity data, multinomial logit regression has been more widely applied. This is primarily because of the need to evaluate multiple integrals of the normal distribution, making the ordered probit model more computationally difficult to estimate (29). As presented in Chapter 3, the multinomial logit model form is as follows:

$$P_n(i) = \frac{e^{\beta X_{in} + \varepsilon}}{\sum_i e^{\beta X_{in} + \varepsilon}}$$

where

$P_n(i)$ represents the probability of a specific crash severity level (i.e., fatal, injury, property damage only)

ε is a random error term assumed to follow a generalized extreme value distribution (29).

Logit models are typically deemed most appropriate for discrete unordered data sets (28).

Both the ordered probit and multinomial logit model forms will be applied as part of this investigation to allow for direct comparison. Determination of the most appropriate model form for this application will consider overall model fit, significance of model variables and any specification issues that arise.

Overall Goodness of Fit

The overall goodness of fit for the two models is measured by ρ^2 values, which indicate the amount of variability in the dependent variables that is described by the independent variables included in the model. ρ^2 values are calculated as follows:

$$\rho^2 = 1 - [\ln L_b / \ln L_0]$$

where L_b is the log-likelihood at convergence and L_0 is the log-likelihood at zero. Values for ρ^2 range between zero and one, where values closer to one indicate a better fit (15).

Significance of Model Variables

A two-sided t-test is used to verify the significance of each model variable. A model variable is considered significant if its estimated coefficient can be concluded to not equal zero at a sufficiently high level of confidence. The level of confidence used for determination of a significant model variable is 95 percent, which corresponds to a t-statistic greater than or equal to ±1.96. A two-sided t-test is required because model variables are significant if their estimated coefficients are either significantly less than zero or significantly greater than zero. This allows for analysis of model factors having both a significant positive relationship to crash severity and a significant negative relationship.

The two-sided t-test assumes a normal distribution for the variation in value of model coefficients resulting from the estimation procedure. The values of model coefficients resulting from the model estimation process vary because of the included error term that accounts for unseen or unmeasured variables that have an additional effect on crash severity. Application of the two-sided t-test to estimated coefficients from the ordered probit model is more easily justifiable due to the assumed normal distribution of its error terms than for the multinomial logit model with assumed generalized extreme value distributed error terms. The two-sided t-test is still applied in evaluation of significance for multinomial logit model variables, as the Central Limit Theorem, which allows the distribution in responses for estimated value to be approximated as normal, justifies it.

Model Comparison

For quantitatively comparing the results of both models, calculations were completed for (1) the predicted severity probability for both models and (2) elasticities for each significant model variable. The effects of several key specification issues were also taken into account.

Predicted Crash Severity. The equations used to calculate the predicted crash severity for each model are presented below. For the ordered probit model:

$$\Pr ob(y=1) = 1 - \Phi(\beta x_n),$$

$$\Pr ob(y=2) = \Phi(\mu - \beta x_n) - \Phi(-\beta x_n),$$

$$\Pr ob(y=3) = 1 - \Phi(\mu - \beta x_n),$$

where:

Φ represents the cumulative normal distribution,

μ represents the threshold value reported in model results, and

all other variables are as previously defined (29).

The probabilities are predicted by setting the x-values for continuous variables at their sample mean and the discrete variables at their sample proportions. Probabilities for the multinomial logit model can be calculated using the basic model from as previously described.

Elasticities. Elasticities were calculated for each significant model variable in order to determine the magnitude of their effect on predicted severity probability. The equations used to determine ordered probit model variable elasticities are as follows:

$$\frac{\partial \Pr ob[y=1]}{\partial x_n} = -\phi(\beta x_n)\beta_i,$$

$$\frac{\partial \Pr ob[y=2]}{\partial x_n} = [\phi(-\beta x_n) - \phi(\mu - \beta x_n)]\beta_i,$$

$$\frac{\partial \Pr ob[y=3]}{\partial x_n} = -\phi(\beta x_n)\beta_i,$$

where:

$\frac{\partial \Pr ob[y=3]}{\partial x_n}$ represents the elasticity for variable-x_n n the PDO crash severity level,

ϕ represents the standard normal density.

β_i represents the estimated coefficient for variable-x_n, and

all other variables are as previously defined (29).

The equations used to calculated elasticities for the multinomial logit model variables are as follows.

For continuous variables:

$$E = [1 - \sum_{I=I_n} P_n(i)]\beta_i x_n,$$

where

E represents the elasticity for the variable x_n at severity level i, and

all other variables are as previously defined (1).

For discrete variables:

$$E = \frac{\exp[\Delta(\beta_i X_n)]\sum_{I}\exp(\beta_i x_n)}{\exp[\Delta(\beta_i X_n)]\sum_{I=I_n}\exp(\beta_i X_n) + \sum_{I\neq I_n}\exp(\beta_i X_n)} - 1,$$

where all variables are as previously defined (1).

Specification Issues. Certain specification issues were taken into account to verify the accuracy of the models developed. These specification issues included the following:

- omission of significant variables,
- presence of irrelevant variables,
- selectivity bias resulting from an incomplete data set,
- multicollinearity effects indicating high correlation among independent variables,
- endogenous variables indicating high correlation between the dependent variable and an independent variable,
- presence of shared unobservables (i.e., Independence of Irrelevant Alternatives).

If any of these specification issues are detected, appropriate countermeasures will be taken to assure the accuracy of model results.

Model Application

Once fully developed, the crash severity model will be used to determine the crash, roadway, traffic, and weather characteristics having a significant effect on crash severity (which is serving as a surrogate indicator of level of safety). While its necessary to consider the effect of all of these factors in combination on crash severity, focus will be placed on the weather-related variables affecting safety levels because (1) roadway and traffic characteristics are less variable over time and hence, would not serve as a good basis for directing response actions and (2) weather-related variables can be predicted, further improving the effectiveness of accurately defined response actions. Specifically, the two-part question to be answered is as follows:

(1) Under what weather-related conditions are motorists most at risk and hence,

(2) when and what response actions should be taken to minimize their risk?

Once action-related guidelines for response personnel, based on current or predicted weather conditions, are in place, over time, both crash severity and frequency should decrease if the proper actions are taken (5).

CHAPTER 4

FINDINGS

This Chapter describes the factors that significantly influence crash severity through the Bozeman Pass Corridor as determined through the development of a statistical crash severity model. Preceding this discussion is a summary of descriptive crash characteristics for the corridor.

Descriptive Statistics

Prior to crash severity model development, general descriptive statistics describing crashes within the project corridor were examined. Data was collected in both directions between Milepost 310 and 340 on Interstate 90. The data extends over a period of six years, from January 1994 to December 1999. Note these descriptive statistics represent only crashes within the project corridor and may not accurately represent national trends. As such, national traffic safety statistics were examined for comparison with these local statistics to establish general differences and similarities between the data sets. Below, descriptive statistics are provided for crash severity, collision type, temporal, environmental, location, and vehicle and driver characteristics as described in Chapter 3.

Crash Severity

Most of the crashes (70 percent) reported through the Bozeman Pass Corridor resulted in property damage only (PDO), although a significant number (29 percent) resulted in injuries. Only one percent resulted in fatalities (see Figure 6). These findings are comparable to the national crash severity statistics for the years 1988 through 1998. Crashes involving at least one fatality represent less than one percent and crashes involving a non-fatal injury represent approximately one-third of total yearly crashes (34).

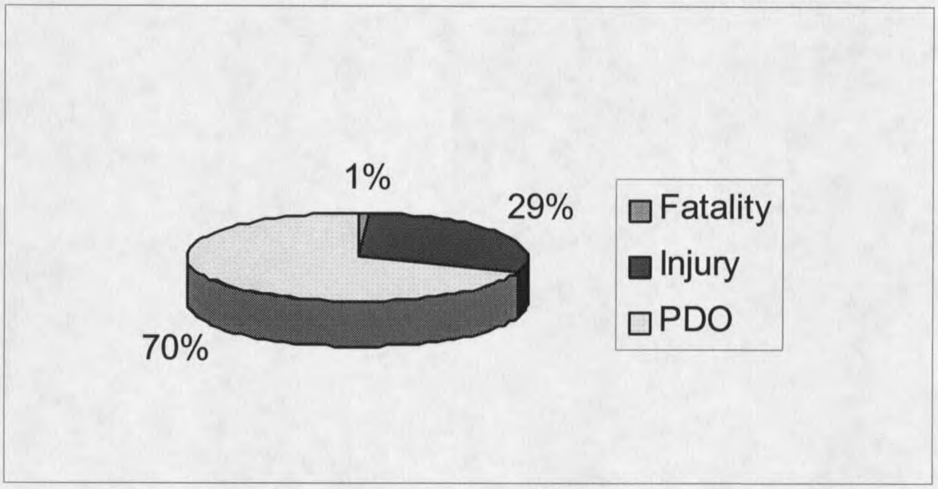

Figure 6. Crash Severity.

Collision Type

The vast majority (82 percent) of reported crashes through the Bozeman Pass Corridor involved single vehicles and were not of a defined major collision type or were unknown (see Figure 7). The roadway classification (i.e., interstate) limits the probability of head on or right angle multiple vehicle collisions, typically associated with the most severe crashes.

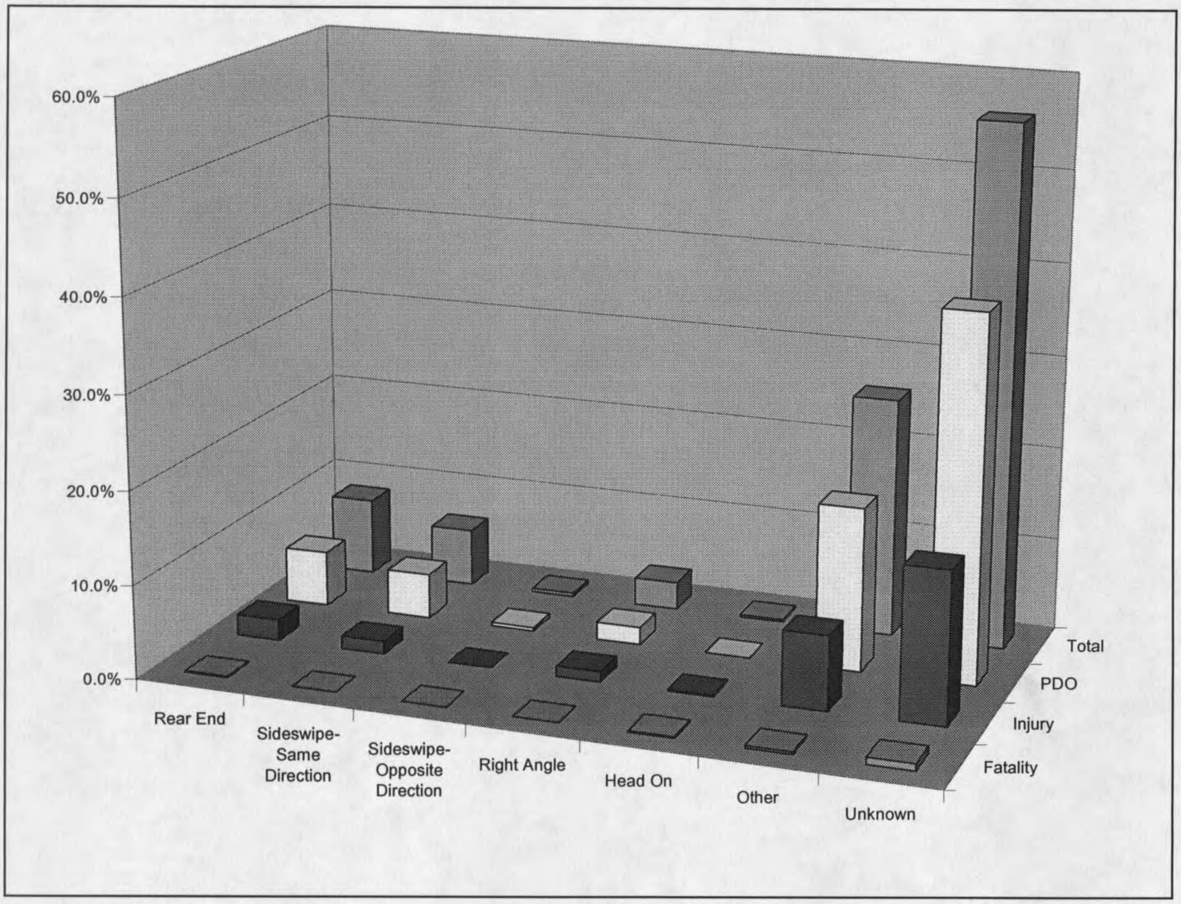

Figure 7. Collision Type.

Temporal Characteristics

Temporal characteristics for the Bozeman Pass Corridor included the percent of crashes occurring each year, month, day of the week and hour of the day for the data spanning January 1994 through December 1999.

Overall, the frequencies of crashes have increased over the six-year period (see Figure 8). As indicated in the figure this increase in crash frequency coincides with an increase in Average Annual Daily Traffic through the Bozeman Pass. The frequency of property damage only crashes has seen the greatest increase while injury and fatality crashes have remained relatively constant over time. Nationally, over the same time span, there was no dramatic change in the total number of crashes, injury crashes or fatality crashes (34). An explanation for the peak in crash frequencies in 1996 is not intuitively obvious.

Not surprisingly, the frequency of crashes is highest during the winter months of October, November, December, January, and February (see Figure 9). These increases are likely due to higher occurrences of pass-related snow, wind, ice and lower visibility. This is in contrast with national statistics, which remained fairly constant between 500,000 and 600,000 crashes per month through 1998 (34). The number of states with more temperate climates likely moderate the seasonal crash fluctuations nationally.

The frequency of local crashes increases during the weekends (see Figure 10). Bozeman Pass serves primarily recreational and commercial travel rather than commuter travel. National statistics for 1998 indicate the effect of increased commuter travel with crashes peaking during the week (34).

Figure 11 shows local crashes by time of day. Crash frequencies peak at noon and decrease significantly from 11:00 p.m. through 5:00 a.m., likely due to low traffic volumes during these times.

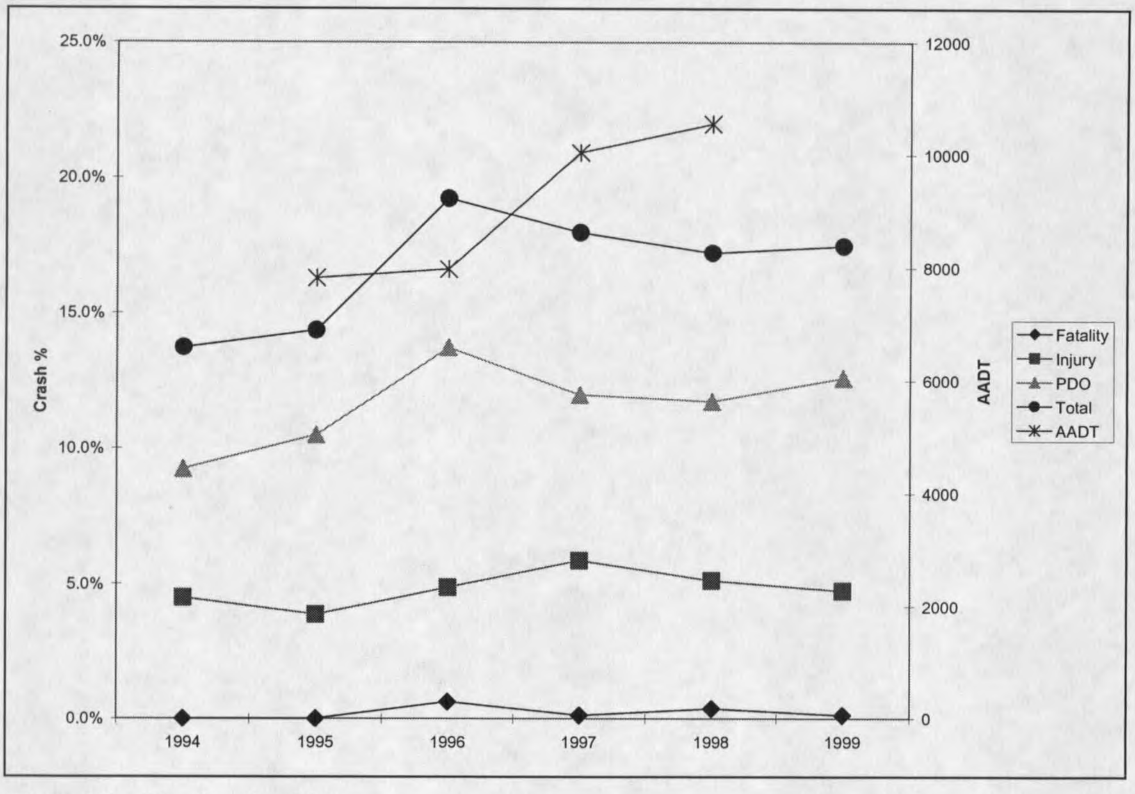

Figure 8. Crashes by Year.

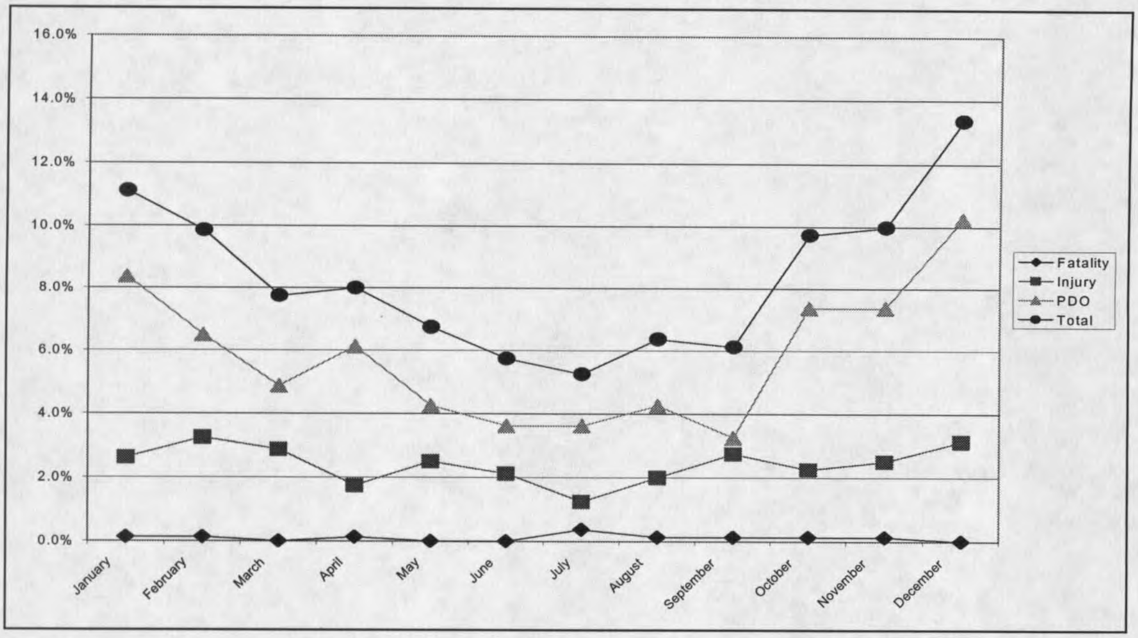

Figure 9. Crashes by Month.

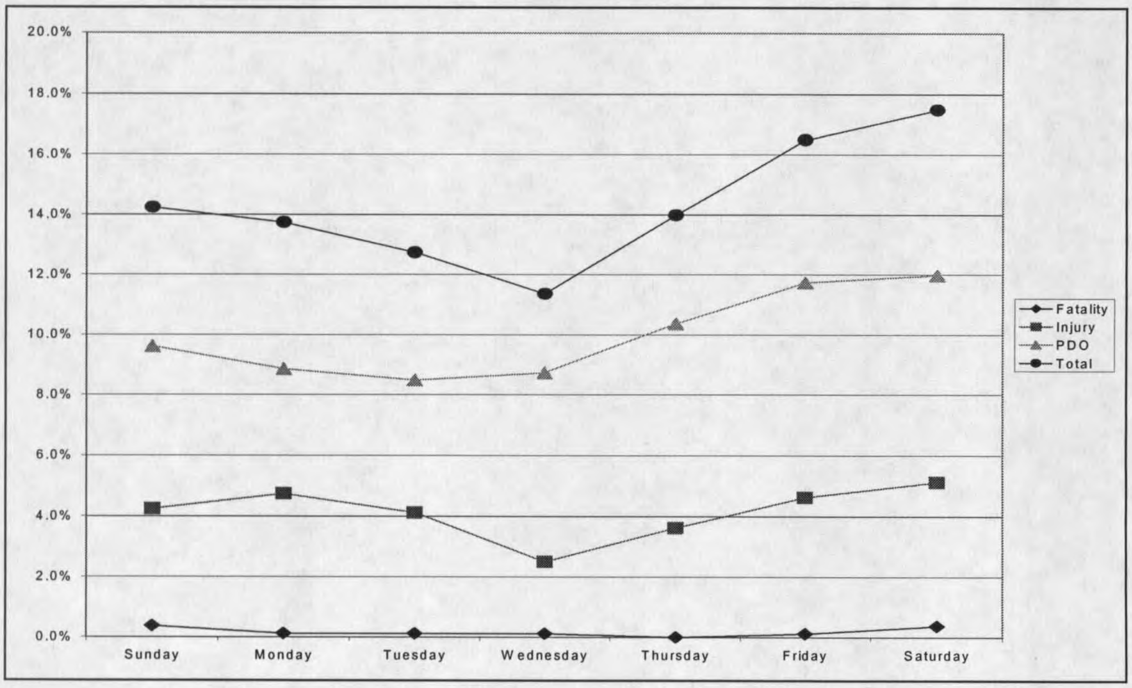

Figure 10. Crashes by Day of Week.

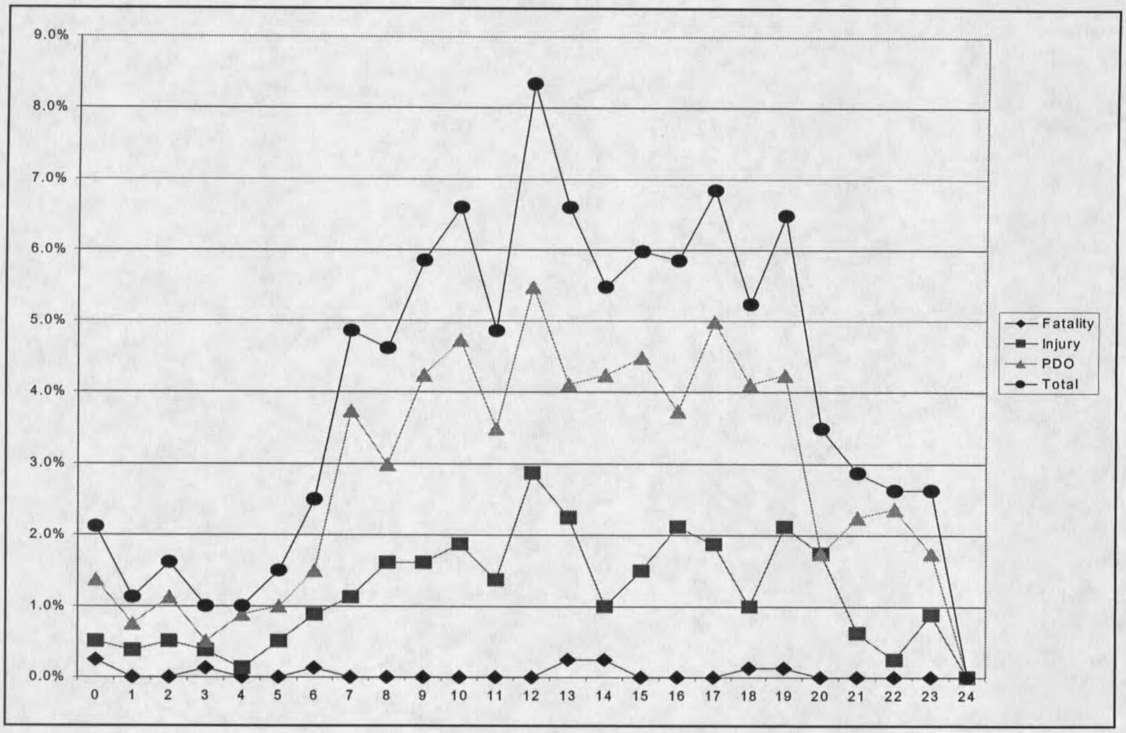

Figure 11. Crashes by Time of Day.

Environmental Characteristics

Environmental characteristics included the light condition at the time of the accident (daylight, dark-not lit, dark-lit, dawn or dusk) and the condition of the roadway surface (dry, wet, snow or slush covered, icy or sand, mud, dirt or oil covered).

The majority (67 percent) of crashes through the Bozeman Pass Corridor occurred during daylight when traffic volumes are highest; 70 percent of crashes nationally also occurred during daylight (see Figure 12). In contrast to the national statistics was the percent of crashes occurring in dark-not lit conditions. Over 20 percent of crashes occurred in dark-not lit conditions locally while only 10 percent occurred under these conditions nationally (34). The rural nature of the Bozeman Pass Corridor, with limited lighting, might account for this.

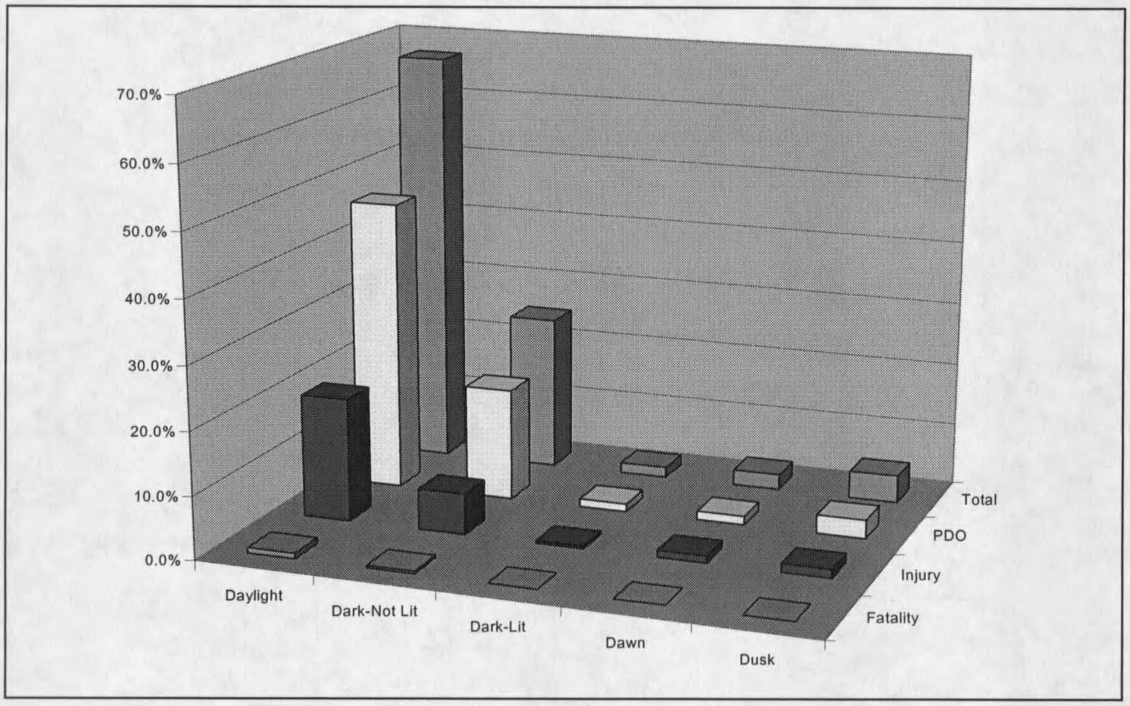

Figure 12. Crashes by Light Condition.

The most prominent discrepancy between local and national crash characteristics is the presence of snow, slush or ice at crash locations (see Figure 13). Nationally, less than three percent of crashes occur on road surfaces covered with snow, slush or ice, while over 50 percent of crashes occur under these conditions in the project corridor (34). This confirms the importance of weather conditions in analyzing crash frequency and severity within the Bozeman Pass Corridor.

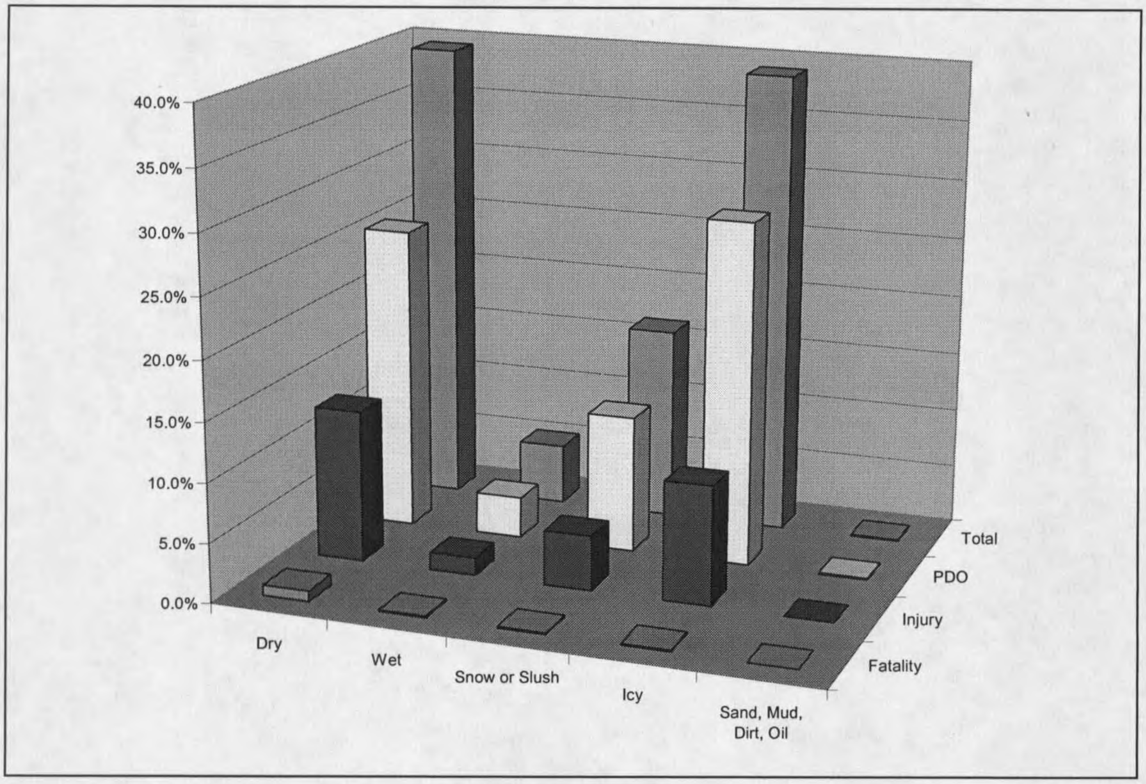

Figure 13. Crashes by Roadway Surface Condition.

Location Characteristics

Location characteristics included the milepost where the crash occurred, position in relation to the roadway and the type of traffic control devices in use.

The majority of local crashes occurred between Milepost 315 and 325 (see Figure 14). The area between Milepost 315 and 325 encompasses Rocky Canyon and Bozeman Hill where more horizontal curves in the roadway exist and the geometry is more constrained.

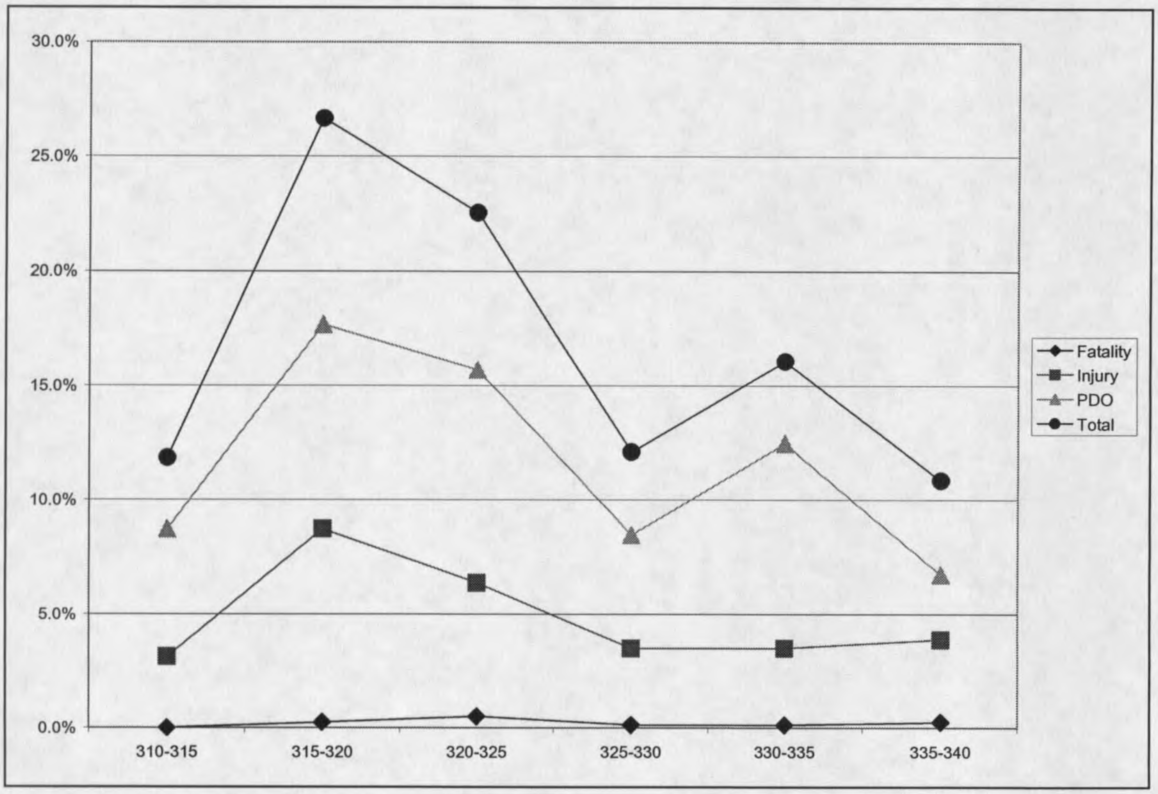

Figure 14. Crashes by Milepost.

As indicated in Figure 15, a plurality (38 percent) of crashes within the Bozeman Pass Corridor occurred on the roadway. National statistics indicate 78 percent of all crashes occurring on-road (34). Significant numbers of local crashes took place off of the roadway leading to the conclusion many crashes resulted from the loss of control of vehicles.

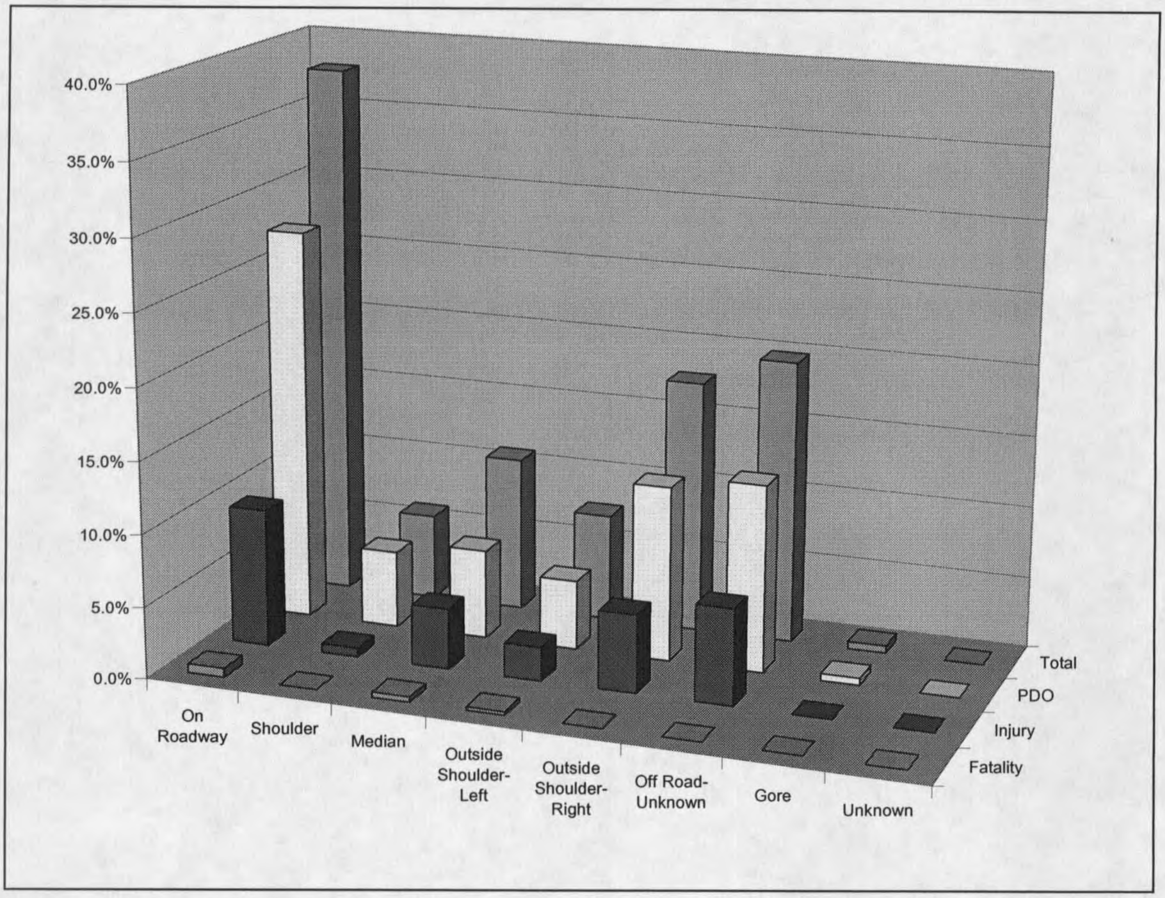

Figure 15. Crashes in Relation to Roadway Location.

Figure 16 describes traffic control devices, such as warning signs, pavement markings, regulatory signs, etc., in place at the crash site. The majority of local crashes occurred in areas where no traffic control devices were in place. Given the rural nature of this corridor and the sparseness of traffic control devices, this is not surprising. Nearly 10 percent of local crashes occurred where warning signs were present. These warning signs describe specific hazards such as sharp curves, strong crosswinds and falling rocks and were likely placed in response to high crash rates at these locations.

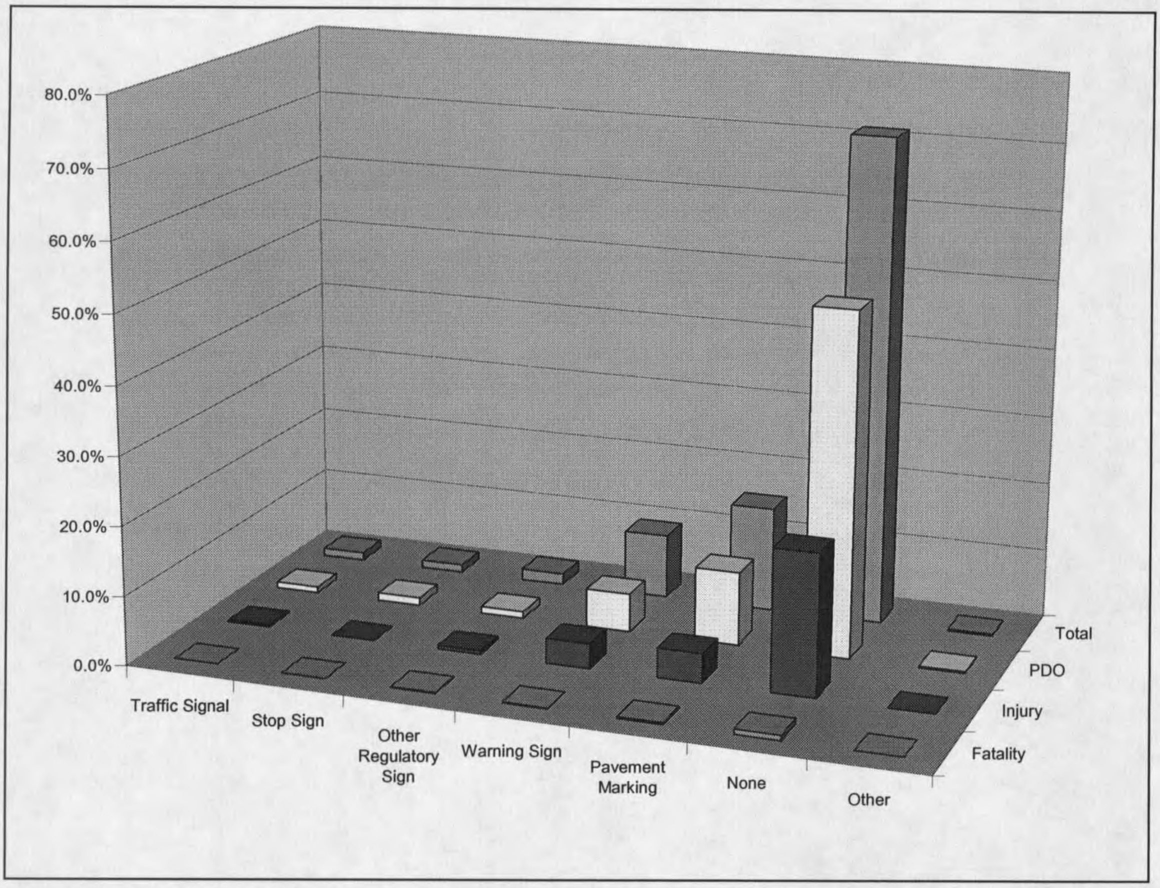

Figure 16. Traffic Control at Crash Location.

Vehicle and Driver Characteristics

Characteristics were examined to determine the type of vehicles involved in crashes and the age and gender of the vehicle's drivers.

The most common vehicle type in the traffic stream and consequently involved in local crashes was passenger cars (see Figure 17). This holds true for all severity levels and is consistent with national statistics. Inconsistent with national statistics was the involvement of large trucks in crashes. Large trucks were involved in 13.6 percent of local crashes compared to 3.6 percent nationally (34). This is indicative of the high amount of commercial traffic using the route. Also higher than national statistics was the involvement of vans, sport utility vehicles and small trucks. This is likely due to the higher use of these vehicles in colder, more mountainous regions than in the rest of the country.

The majority (37 percent) of drivers involved in a crash between 1994 and 1999 were between the ages of 16 and 30 years old. This is true for all levels of severity and is in agreement with national statistics (see Figure 18). The percentage of local crashes involving male or female drivers is also in agreement with national statistics, with a strong majority (66 percent) of male drivers in crashes (see Figure 19) (34).