Pergamon

Accid. Anal. and Prev., Vol. 28, No. 3, pp. 391–401, 1996

0001-4575/96 $15.00 + 0.00

S0001-4575(96)00009-7

STATISTICAL ANALYSIS OF ACCIDENT SEVERITY ON RURAL FREEWAYS

VENKATARAMAN SHANKAR[1], FRED MANNERING[1] and WOODROW BARFIELD[2]

[1]Departments of Civil Engineering and [2]Industrial Engineering, University of Washington, Seattle, WA 98195, U.S.A.

(Accepted 10 August 1995)

Abstract—The growing concern about the possible safety-related impacts of Intelligent Transportation Systems (ITS) has focused attention on the need to develop new statistical approaches to predict accident severity. This paper presents a nested logit formulation as a means for determining accident severity given that an accident has occurred. Four levels of severity are considered: (1) property damage only, (2) possible injury, (3) evident injury, and (4) disabling injury or fatality. Using 5-year accident data from a 61 km section of rural interstate in Washington State (which has been selected as an ITS demonstration site), we estimate a nested logit model of accident severity. The estimation results provide valuable evidence on the effect that environmental conditions, highway design, accident type, driver characteristics and vehicle attributes have on accident severity. Our findings show that the nested logit formulation is a promising approach to evaluate the impact that ITS or other safety-related countermeasures may have on accident severities. Copyright © 1996 Elsevier Science Ltd

Keywords—Nested logic, Accident injuries, Highway safety

INTRODUCTION

The forthcoming implementation of Intelligent Transportation Systems (ITS) has given rise to concerns relating to the impact of such systems on vehicular safety. While ITS have elements that are common to more traditional safety-oriented countermeasures, they present unique technological and human factors concerns that must be dealt with. Addressing these additional concerns does not present an unusually difficult conceptual or methodological problem, but it does necessitate that consideration be given to the wide-range of factors that may affect overall safety.

In measuring the impact of an ITS on overall vehicular safety, it is important to establish defensible safety-measurement criteria. Past safety-related research has shown that the frequency and severity of accidents are two such measurement criteria. In our earlier paper (Shankar et al. 1995) we addressed accident frequencies as they relate to ITS. This paper will deal exclusively with accident severities.

Previous research on accident severity has been diverse and provided important methodological and behavioral insights. Several accident-severity studies conducted have examined particular severity types such as fatalities (Shibata and Fukuda 1994) or concentrated on crashes involving certain vehicle types such as trucks (Golob et al. 1987; Alassar 1988). Other studies have concentrated on enforcement issues and their impact on fatal vehicular crashes related to alcohol and seat belt use (see for example Evans 1986, 1990; Holubowycz et al. 1994). Such studies have placed a heavy emphasis on the impact of human factors in determining accident severity. However, other elements, such as highway design and environmental conditions, while not receiving the extensive attention given to human factors, have also been recognized as important determinants of accident severity (see Mercer 1986; Massie et al. 1993). Overall, past research has provided important insights into the range of factors that influence accident severity.

From a methodological standpoint, a variety of approaches have been employed to study accident severity. Using logistic regression techniques, Jones and Whitfield (1988) modeled severity risk as a function of anthropometric measures, car mass, age of driver and restraint system use. Logistic regression was also employed in a study of driver fatalities to model the probability of fatalities conditioned on the occurrence of an accident (Lui et al. 1988). However, the study used a limited number of variables such as driver age, gender, impact points, vehicle crash severity, restraint system use and car mass. Other important aggravating factors such as inclement weather, location of accident (for example, whether the accident occurred on a curve, or off the road) were omitted. Other studies have employed multivariate time-series approaches to successfully develop predictive models of accident severity (Lassarre 1986). Evans (1990) employed a double-pair comparison approach to examine how occupant characteristics affect fatality risk. Still other methodologies such as headway-based severity analysis (Glimm and Fenton 1980), bivariate probit analysis (Hutchinson 1986) and discriminant analysis (Shao 1987) have been used. The latter methodologies, especially the probit and discriminant analyses, allow the researcher to model severity in terms of thresholds. These threshold approaches are consistent with the general categorization of accident severity as being either property damage only, possible injury, evident injury, or disabling injury/fatality.

The present study attempts to extend the empirical and methodological contributions of previous work by developing a predictive model of accident severity that can be used to evaluate the safety-related impacts of ITS and other safety-related countermeasures. In so doing, we will address highway design and environmental issues, along with human factors, in a multivariate context using a nested-multinomial logit approach. The empirical focus of our work will be a rural section of Interstate 90 (I-90) in Washington State, which is scheduled to have an ITS operational in Autumn 1996.* The section of highway selected is roughly 61 km in length and is located 50 km east of Seattle. The highway is a high-accident area due to its complex roadway geometrics and adverse climatic conditions (it crosses the Cascade mountain range). This paper proposes to study past accident severities on this highway in an effort to establish a basis from which the safety effectiveness of the forthcoming ITS can be evaluated. This work follows our previous effort on accident frequencies (Shankar et al. 1995). In combination with models of accident frequencies, the severity models presented in this paper will enable us to provide a complete assessment of the possible safety impacts of the forthcoming Interstate-90 ITS.

Our paper begins with a discussion of the proposed methodological approach. This is followed by a description of the study area and the data used in model estimation. We then present model estimation results and a detailed discussion of our findings and their implications for accident severity analysis. The paper concludes with a summary and directions for future research.

*This ITS will consist of a series of variable message signs (warning drivers of adverse weather and traffic conditions), variable speed limit signs (that will change the speed limits in response to climatic and traffic conditions), and equipping several hundred vehicles with in-vehicle climate and traffic condition warning devices.

METHODOLOGY

We begin by developing a conditional model of accident severity (i.e. conditioned on the fact that an accident has occurred).† Severity of an accident is specified to be one of four discrete categories: (1) property damage only, (2) possible injury, (3) evident injury, and (4) disabling injury or fatality.‡ Given these four discrete categories, a statistical model that can be used to determine the probability of an accident having a specific severity level can be derived. We start the derivation with the following probability statement,

$$P_n(i) = P(S_{in} \geqslant S_{In}) \; \forall I \neq i \tag{1}$$

where $P_n(i)$ is the probability that accident n is severity i, P denotes probability and S_{in} is a function of covariates that determine the likelihood of accident n being severity i (I is the set of possible severities). To estimate this probability, a function defining the severity likelihoods must be specified. We use a linear form such that,

$$S_{in} = \boldsymbol{\beta}_i \mathbf{X}_n + \varepsilon_{in} \tag{2}$$

where $\mathbf{X}_n$ is a vector of measurable characteristics that determine the severity (e.g. driver age, driver gender, highway design attributes, prevailing weather conditions, vehicle type, use of seat belts, and so on), $\boldsymbol{\beta}_i$ is a vector of estimable coefficients, and ε_{in} is an error term that accounts for unobserved factors influencing accident severity. The term $\boldsymbol{\beta}_i\mathbf{X}_n$ in this equation is the observable component of severity determination because the vector $\mathbf{X}_n$ contains measurable variables (e.g. highway design attributes at the location of accident n), and ε_{in} is the unobserved portion.

Given equations (1) and (2), the following can be written,

$$P_n(i) = P(\boldsymbol{\beta}_i\mathbf{X}_n + \varepsilon_{in} \geqslant \boldsymbol{\beta}_I\mathbf{X}_n + \varepsilon_{In}) \; \forall I \neq i \tag{3}$$

or,

$$P_n(i) = P(\boldsymbol{\beta}_i\mathbf{X}_n - \boldsymbol{\beta}_I\mathbf{X}_n \geqslant \varepsilon_{In} - \varepsilon_{in}) \; \forall I \neq i \tag{4}$$

With equation (4), an estimable severity model can be derived by assuming a distributional form for the

†For a statistical model of the likelihood of an accident occurring, the reader is referred to our earlier work on accident frequencies (Shankar et al. 1995).

‡The determination of this severity is made by the officer at the scene of the accident and reported on the Washington State accident report forms. Also note that accidents are classified based on the most severe consequence of the accident. For example, an accident resulting in both injury and death will be classified as a fatality accident. In addition, it must be noted that total number of classified accidents reported is less than or equal to the number of individual severities since, for example, an injury accident may result in more than one person being injured.

error term. A natural choice would be to assume that this error term is normally distributed. Such an assumption results in a probit model. However, probit models are computationally difficult to estimate (see Ben-Akiva and Lerman 1985). A more common approach for models of this type is to assume that ε_{in}'s are generalized extreme value (GEV) distributed.* The GEV assumption produces a closed form model that can be readily estimated using standard maximum likelihood methods. It can be shown (McFadden 1981) that the GEV assumption produces the simple multinomial logit model,

$$P_n(i)=\exp[\boldsymbol{\beta}_i\mathbf{X}_n]/\sum_I \exp[\boldsymbol{\beta}_I\mathbf{X}_n] \tag{5}$$

where all variables are as previously defined and the vector $\boldsymbol{\beta}_i$ is estimable by standard maximum likelihood methods.

Unfortunately, the simple multinomial logit model presented in equation (5) can lead to serious specification problems because this particular form requires us to assume that the unobserved terms (ε_{in}'s) are independent from one severity type to another. This is not likely to be the case because some of the severity types are likely to share unobserved terms and thus be correlated. For example, property damage only and possible injury accidents may share unobservables such as internal injury or effects associated with lower-severity accidents. In the presence of shared unobservables, the logit formulation will erroneously estimate the coefficient vector and severity probabilities. To circumvent this problem, a more generalized form of the severity probabilities can be derived from the GEV distribution. This is referred to as a nested logit model and has the following form (see McFadden 1981),

$$P_n(i)=\exp[\boldsymbol{\beta}_i\mathbf{X}_n+\Theta_i L_{in}]/\sum_I \exp[\boldsymbol{\beta}_i\mathbf{X}_n+\Theta_i L_{In}] \tag{6}$$

$$P_n(j|i)=\exp[\boldsymbol{\beta}_{j|i}\mathbf{X}_n]/\sum_J \exp[\boldsymbol{\beta}_{j|i}\mathbf{X}_n] \tag{7}$$

$$L_{in}=\ln\left[\sum_J \exp(\boldsymbol{\beta}_{j|i}\mathbf{X}_n)\right] \tag{8}$$

where $P_n(i)$ is the unconditional probability of accident n having severity i (e.g. evident injury), $P_n(j|i)$ is the probability of accident n having severity j conditioned on the severity being in severity category i (e.g. the probability of having property damage only or possible injury given that there was no evident injury), J is the conditional set of severity categories (conditioned on i) and I is the unconditional set of severity categories, L_{in} is the inclusive value (log sum) which is interpreted as the expected maximum value of the attributes that determine severity probabilities in severity category i, Θ_i is an estimable coefficient which must have a value between zero and one to be consistent with the model derivation (see McFadden 1981).

The structure of the nested logit model eliminates the adverse consequences of shared unobservables because logit models determine probabilities using the difference in functions defining severity (i.e. the S_{in}'s in equation 2). Thus when a logit nest contains only those severity levels that share unobserved effects, the unobserved effects will cancel in the differencing and thereby preserve the assumption of independence needed to derive the model. We will discuss estimation concerns relating to this model and show its suitability for analyzing accident severities in the model estimation section of this paper. For further information on the derivation and application of nested logit models the reader is referred to Ben-Akiva and Lerman (1985), Train (1986) and Mannering and Winston (1985, 1991, 1995).

EMPIRICAL SETTING

In collecting data on the 61 km study section of I-90, six data categories were specified; (1) individual accident data from the Washington State Department of Transportation (WSDOT), (2) weather data, (3) geometric data, (4) pavement surface data, (5) vehicle data and (6) driver-related data. For the purposes of classifying roadway geometric data, the study area was segmented into 10 equal 6.1 km sections (see Shankar, Mannering, and Barfield 1995). Important accident data included information on primary identified causes, most severe consequence of the accident, time of day of accident, accident location with respect to the traveled way (on or off the roadway, whether the accident occurred on a curve or straight section or a grade). Roadway illumination information, types of roadside objects involved in collision, and accident type. Weather data included whether or not the accident occurred during rainy, snowy, or foggy conditions. The geometric data included (for the section of highway in which the accident occurred) radii of horizontal curves, vertical grades, number of horizontal and vertical curves per kilometer, percentage length of horizontal curves.

*Discriminant analysis is another alternative to the approach that we have selected to model accident severity (Shao 1987). However, several studies have shown (see, for example, Press and Wilson 1978), that logit-based modeling approaches (which include the GEV approach) are superior to discriminant analysis for classification primarily because of the violation of the assumption of normality of disturbances in discriminant analysis. Presence of non-normal variables such as qualitative variables (dummy variables) in classification studies causes such a violation. In the present study, several qualitative variables, as will be shown, play significant roles in the determination of accident severity.

Table 1. Accident severity distribution by key variables

Accident conditioning variable	Severity frequency: Property damage	Possible injury	Fatality	Evident injury	Disabling injury
Daylight (excluding dawn and dusk)	609	135	6	31	126
Night	353	53	3	27	64
Drunk–driving	31	1	2	2	9
Sober driving	989	203	8	61	199
Horizontal curve	410	76	8	25	88
Straight section	610	128	2	38	120
Single-vehicle collision	587	99	5	44	128
Two-vehicle collision	377	91	4	16	67
Multi-vehicle collision (greater than two vehicles)	56	14	1	3	13

Pavement surface data included information on whether the accident occurred on icy, snowy, wet or dry pavement. Vehicle data included information on number and type of vehicles, restraint system* used by driver and occupants at the time of the accident, ejection status of occupants (i.e. whether or not occupants have been ejected from the vehicle) and number of occupants in each vehicle. Driver-related data included information on driver sobriety at the time of accident, and driver ages and gender.

Accident data for the 5-year period between 1988 and 1993 was used to estimate accident severities. A total of 1505 individual vehicular accidents† reported during this period were used in this study, with 1020 of those accidents resulting in property damage only.‡ Out of the remaining 485 accidents, 10 were fatality collisions, 63 evident injury and 208 disabling injury collisions. Table 1 provides additional information on the distribution of severity by important variables such as daytime/night, sobriety, accident location (horizontal curve as opposed to a straight section), and number of vehicles involved in the collision.

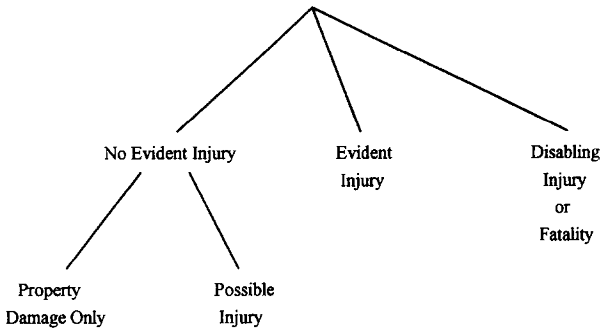

Fig. 1. Nested structure of accident severities.

MODEL ESTIMATION

To estimate the nested logit model specified in equations (6), (7), and (8), we use a sequential estimation procedure. In this procedure, the lower conditional level of the nest (equation 7) is estimated as a simple multinomial logit (MNL) model using standard maximum likelihood methods and the estimated coefficients are used to compute the inclusive value of that level (i.e. L_{in} in equation 8). The next step involves estimating the higher level nest treating it as a simple MNL form but conditioning it on the estimated coefficients of the lower nest. This is done by introducing the computed value of L_{in} for the lower nest as an explanatory variable. All possible nested structures (which examine possible correlation among the unobserved effects of various severity levels) were considered. Statistically, as measured by likelihood ratio tests, the structure shown in Fig. 1 proved to be the correct model form.§ This nesting

*Although this information is subject to bias based on when the reporting officer arrives at the scene, uncertainty about restraint system use significantly diminishes in the case of injury-related accidents in which subjects are incapacitated to the extent of being unable to remove their restraint systems. In the case of property damage and possible injury accidents, the significance of restraint system use is minimal. In this context, it must be noted that uncertainty about restraint system use generally results in information on restraint system use being coded "restraint system use not known".

†A total of 2225 individual accidents were reported for the 65-month period between January 1988 and May 1993. However, weather data corresponding to 720 accidents was not available because of equipment failure or faulty operation. Also, it is important to note that our data were obtained only from reported accidents. It is likely that many accidents (particularly those that are minor in severity) may go unreported. This means that our accident sample is not a random sample of all accidents. Fortunately this will have a minimal impact on model estimation results. In fact, all coefficients will be correctly estimated with the exception of the constant terms. If the number and severity of unreported accidents were known, the three constant terms reported in this paper could be adjusted by a simple calculation and no additional estimation would be necessary (see Ben-Akiva and Lerman (1985) for details on such stratified-sample adjustments).

‡As mentioned previously, accident classification is based on the most severe consequence of the accident.

§We also tested this specification for possible correlation among unobservables using the specification test developed by Small and Hsiao (1985). The tests showed that this specification does not have statistically significant specification error.

Table 2. Estimation of property damage and possible injury probabilities conditioned on the occurrence of a non-injury accident

Variable	Estimated coefficient	t-Statistic
Constant (specific to property damage alone)	3.1950	5.19
Overturn accident indicator (1 if accident type was "single-vehicle overturn", 0 otherwise; specific to possible injury)	1.3993	3.49
Rear-end accident indicator 1 (1 if accident type was "rear-end" accident and occurred on wet pavement, 0 otherwise; specific to possible injury)	0.4351	1.00
Rear-end accident indicator 2 (1 if accident type was "rear-end" accident and involved exactly two vehicles, 0 otherwise; specific to possible injury)	1.3415	5.00
Percentage of horizontal curve length per kilometer of roadway (specific to possible injury)	0.0141	1.37
Number of horizontal curves per kilometer of roadway (specific to possible injury)	0.4931	1.94
Illumination indicator (1 if surroundings were dark with no street lights present, 0 otherwise; specific to property damage)	0.3271	1.72
Sideswipe accident indicator (1 if accident type was "sideswipe" involving more than two vehicles, 0 otherwise; specific to possible injury)	1.2686	1.74
Same-direction accident indicator (1 if accident type was "same-direction" involving more than two vehicles, 0 otherwise; specific to possible injury)	1.0640	2.07
Fixed object accident indicator (1 if accident type was "fixed object", 0 otherwise; specific to possible injury)	1.0597	3.14
Icy pavement indicator (1 if accident occurred on icy pavement and involved only one vehicle, 0 otherwise; specific to property damage alone)	0.5323	2.11
Single-vehicle collision indicator (1 if accident involved on vehicle, 0 otherwise; specific to property damage)	0.6490	1.91
Number of observations	1224	
Log-likelihood at zero	−848.41	
Log-likelihood at convergence	−518.40	
ρ^2	0.39	

indicates that the property damage only and possible injury severity levels shared unobserved terms that would have caused a serious model specification error had a simple multinomial logit model been estimated (as shown in equation 5).

Maximum likelihood estimation results are presented in Tables 2 and 3. Table 2 presents the estimation of the lower nest (property damage only and possible injury)* and Table 3 shows the estimation of the overall model of accident severity (upper nest). The inclusive value coefficient of 0.4153 with its t-statistic of 2.6391 suggests that shared unobservables are significantly present between property damage only and possible injury alternatives.† Both models resulted in good statistical fits,‡ with the lower level of the nest showing a ρ^2 of 0.39 and the overall model a ρ^2 of 0.52.

Turning first to the coefficient estimates of the lower nest (i.e. property damage only and possible injury conditioned on the accident having no evident injuries) we find that all variable coefficients included in the specification are statistically significant and have plausible signs. The implications of each of the coefficient estimates is discussed below.

Variable: Overturn accident indicator
Finding: Greater probability of possible injury relative to property damage only
The "single-vehicle" overturn accident indicator's positive coefficient indicates a greater likelihood of possible injury than property damage only. This shows that single-vehicle accidents with no evident injury tend to be more severe in nature.

Variable: Wet-pavement rear-end accident indicator

*Possible injury accidents (which may seem a somewhat vague category) are determined at the scene by Washington State troopers using well-defined, uniformly taught identification procedures. Our testing of various model structures suggests that this is a unique severity category and must be considered separately (i.e. even though the accident will eventually be classified as an injury or property damage only accident).

†If no correlation between these unobserved terms was present, the coefficient value would not be significantly different from one. When the coefficient value of the inclusive value term is equal to one, the nested logit structure reduces to the simple multinomial structure as shown in equation (5).

‡ρ^2 is defined as $1\text{-}[L(\beta)/L(0)]$ where $L(\beta)$ is log-likelihood at convergence and $L(0)$ is initial log-likelihood when all parameters are set to zero. A modified form of ρ^2 is the adjusted ρ^2 that takes into account the number of parameters included and is given by $1\text{-}[(L(\beta)\text{-}K)/L(0)]$, where K is the number of parameters. The adjusted ρ^2 for the two models were determined to be 0.38 and 0.50 respectively.

Table 3. Estimation of overall nested logit model of accident severity probabilities

Variable	Estimated coefficient	t-Statistic
Constant (specific to evident injury)	−2.8468	−3.53
Constant (specific to disabling injury/fatality)	−2.4882	−4.78
Angle accident type indicator (1 if accident type is "angle", 0 otherwise; specific to evident injury and disabling injury/fatality)	1.5813	1.97
Overturn accident type indicator (1 if accident type is "overturn", 0 otherwise; specific to disabling injury/fatality)	0.5192	2.24
Speeding indicator 1 (1 if "exceeding posted speed" was primary cause, 0 otherwise; specific to evident injury)	0.9640	1.72
Speeding indicator 2 (1 if "exceeding reasonable safe speed for conditions" was primary cause, 0 otherwise; specific to evident injury)	−0.8855	−2.57
Speeding indicator 3 (1 if "exceeding reasonable safe speed for conditions" was primary cause, 0 otherwise; specific to disabling injury/fatality)	−0.3160	−1.69
Restraint system use indicator (1 if a restraint system was not in use by at least one driver involved in collision, 0 otherwise; specific to evident injury and disabling injury/fatality)	0.6376	2.72
Occupant ejection indicator (1 if any occupant was partially or totally ejected, 0 otherwise; specific to evident injury)	2.0070	3.78
Gender of driver (1 if all drivers involved in collision were male; 0 otherwise; specific to disabling injury/fatality)	1.0008	2.12
Percentage of horizontal curves per kilometer of roadway (specific to evident injury and disabling injury/fatality)	0.0302	3.39
Number of horizontal curves per kilometer of roadway (specific to no evident injury and disabling injury/fatality)	0.7204	1.93
Curve–sobriety interaction (1 if accident occurred on a horizontal curve and at least one driver involved was identified as "had been drinking and alcohol-impaired," 0 otherwise; specific to disabling injury/fatality)	1.2755	2.31
Snow-covered pavement indicator 1 (1 if accident occurred on snow-covered pavement, 0 otherwise; specific to evident injury)	−0.9450	−2.51
Snow-covered pavement indicator 2 (1 if accident occurred on snow-covered pavement, 0 otherwise; specific to disabling injury/fatality)	−0.5310	−2.86
Vehicle-mass difference indicator (1 if accident involved collision of a single truck and a single passenger car, 0 otherwise; specific to evident injury and disabling injury/fatality)	0.5214	1.83
Accident location indicator 1 (1 if accident occurred off the road, 0 otherwise; specific to evident injury)	1.2054	3.81
Accident location indicator 2 (1 if accident occurred off the road, 0 otherwise; specific to disabling injury/fatality)	0.5118	2.54
Age–sobriety interaction (1 if all drivers involved in accident were older than 55 years and at least one driver involved was identified as "had been drinking and alcohol-impaired," 0 otherwise; specific to evident injury)	1.6541	1.34
Night-time–pavement interaction (1 if accident occurred at night and on icy pavement, 0 otherwise; specific to evident injury and disabling injury/fatality)	0.2475	1.00
Fixed object–horizontal curve interaction (1 if accident type was "fixed-object" and occurred on a horizontal curve, 0 otherwise; specific to disabling injury/fatality)	0.4580	1.99
Fixed object–icy pavement interaction (1 if accident type was "fixed object" and occurred on icy pavement, 0 otherwise; specific to no evident injury)	0.5606	2.21
Inclusive value of property damage and possible injury (L_{in}, specific to no evident injury)	0.4153	2.64
Number of observations	1505	
Log-likelihood at zero	−1653.4	
Log-likelihood at convergence	−802.3	
ρ^2	0.52	

Finding: Greater probability of possible injury relative to property damage only

This variable captures the effect of rear-end accidents occurring in rainy weather. Such weather conditions make vehicles in front more difficult to see and increase the distance required to stop. It may also be argued that inclement weather may lower driver speeds and reduce risk of possible injury to a statistically insignificant level. However, intermittent and light rainfall, in spite of making the pavement wet and slippery, may not be dense enough to significantly lower driver speeds. The rear-end accident indicator may be capturing the effect of higher-than-expected vehicle speeds at the time of impact.

Variable: Two-vehicle rear-end accident indicator
Finding: Greater probability of possible injury relative to property damage only
While the previous finding reflects rear-end accidents in general, this variable captures the effect of two-vehicle collisions only. This coefficient is highly significant, statistically, indicating that injury, though not evident such as disabling, may be internalized to a greater extent than previously thought in such collisions. It is speculated that one important factor relating to the high significance of this variable could be the dissipation of kinetic energy and momentum per vehicle. The lower the number of vehicles involved, the greater the impact on each vehicle, thus increasing the likelihood of internal injuries, such as whiplash, which would be coded at the scene of the accident as a possible injury. The significantly higher coefficient (1.415 vs 0.4351 for the previous variable) corroborates the effect of inclement weather on driver speeds.

Variable: Percentage of horizontal curve length per kilometer of roadway
Finding: Greater probability of possible injury relative to property damage only
This variable captures the effect of terrain on the severity of an accident with no evident injuries. The high proportion of horizontal curves was found to increase the likelihood of a possible injury accident.

Variable: Number of horizontal curves per kilometer of roadway
Finding: Greater probability of possible injury relative to property damage only
This variable further confirms the finding offered by the curve-length variable. A greater number of curves on a particular section of roadway, although in some cases a speeding-deterrent, will affect steering control and reduce sight distance and thus be more likely to result in a possible injury collision.

Variable: Illumination indicator
Finding: Night-time conditions with no street lights present increase the probability of property damage only
This variable is likely an artifact of roadway design practices. Since the most dangerous portion of the road are the likely to be illuminated, we would expect a positive correlation between the absence of illumination and the likelihood of a property damage only accident.

Variable: Sideswipe accident indicator
Finding: Greater probability of possible injury relative to property damage only in multi-vehicle accidents
This variable (sideswipes involving more than two vehicles) primarily captures the exposure to possible injury. If the number of vehicles involved in a sideswipe accident exceeds two, the exposure increases in terms of number of occupants involved in the accident. Thus the greater likelihood of possible injury. This variable may also be capturing the level of severity generally associated with this type of accident.

Variable: Same-direction accident indicator
Finding: Greater probability of possible injury relative to property damage only in multi-vehicle accidents
This variable (same direction accidents involving more than two vehicles) further illustrates the exposure, in terms of the number of occupants likely to be involved in the accident, that was also attributed to the sideswipe accident indicator. The finding is consistent with previous findings on the relationship of possible injury to increased exposure.

Variable: Fixed-object accident indicator
Finding: Greater probability of possible injury relative to property damage only
This variable is consistent with intuition which suggests that given that an accident resulted in no evident injuries, there is a greater probability of suffering possible injury from collisions with fixed objects. It must be noted that this applies only to accidents resulting in no evident injuries.

Variable: Icy pavement indicator
Finding: Greater probability of property damage only relative to possible injury
This finding suggests that for single-vehicle accidents that occur on icy pavements, property damage will occur with greater probability than possible injury. This finding is consistent with previous conclusions on exposure in terms of number of vehicles involved and illustrates the effect of icy conditions. While icy pavement conditions hinder braking and steering control, they also tend to lower vehicle speeds. This effect reduces the risk of possible injury and limits the severity of an accident to property damage only.

Variable: Single-vehicle collision indicator
Finding: Greater probability of property damage only relative to possible injury
This finding corroborates earlier observations that fewer involved-vehicles increase the likelihood of property damage only. It also provides an important severity measure for accidents involving only one vehicle.

We now turn our attention to the estimation results of the overall model as presented in Table 3. The interpretation of coefficient estimates is provided below.

Variable: Angle accident type indicator
Finding: Greater probability of evident injury or disabling injury/fatality than no evident injury*
In a freeway corridor, angle accidents can occur when a leading vehicle is turned sideways positioning it at angle to the flow of following traffic, thereby making severe collisions more likely. Angle accident indicators may also be acting as surrogates for factors such as black ice which are not strictly observed due to weather data limitations.

Variable: Overturn accident indicator
Finding: Greater probability of evident injury or disabling injury/fatality
This finding corroborates the finding documented for "single-vehicle" overturn effects in the lower level model. After correcting for single-vehicle effects which are incorporated in the no evident injury category, we observe that overturns result in a greater probability of evident injury or disabling injury/fatality.

Variable: Speeding indicator 1 (exceeding posted speed limit)
Finding: Greater probability of evident injury relative to no evident injury or disabling injury/fatality
This finding isolates the effect of speeding over posted speed limits on accident severity. Current knowledge and intuition suggest that speeding is a primary cause in severe accidents such as those resulting in disabling injury/fatality. However, there are associated factors such as number of curves in a section, sobriety and age which confound the effects of speed. Controlling for these factors may uncover specific effects of speed in isolation. In the present model, we control for all such factors (as discussed below) and isolate the effects of speed.

Variable: Speeding indicators 2 and 3 (exceeding safe speed for prevailing conditions)
Finding: Greater probability of no evident injury relative to evident injury or disabling injury/fatality
This finding illustrates an important distinction in the effects of high and low speeds in that it examines the impact of low speeds on severity. By examining speed-related effects in accidents where exceeding the posted limit was the primary cause, we essentially restrict the population of accidents related to speed to above the speed limit (104 km/hr). The variable under discussion examines the effect of speeds over the range of possible speeds below the speed limit.* As mentioned previously, several factors interact in association with speed and aggravate its effect. For speeds under the posted limit but exceeding reasonable speeds for prevailing conditions, aggravating factors typically include weather-related variables such as pavement surface conditions, age, and grade or curve-related factors. As discussed in a later section, we control for these factors and isolate the effect of exceeding safe speeds for prevailing conditions. Isolating the effect of safe speeds indicates that at lower speeds, it is more likely that the accident will have no evident injury. This finding† illustrates the importance of a more comprehensive model specification for providing better insights into underlying processes.

Variable: Restraint system use indicator
Finding: Greater probability of evident injury or disabling injury/fatality relative to no evident injury if at least one driver did not use a restraint system at the time of the accident
This finding is in agreement with other studies (Evans 1986). An interesting observation was that separating the restraint system used by driver and passengers did not yield significantly different coefficients for passengers.‡

Variable: Occupant ejection indicator
Finding: Greater probability of evident injury relative to no evident injury or disabling injury/fatality
This finding indicates that after controlling for factors such as overturn collisions or run-off-the road accidents, ejection of the occupant (partial or total) will result in a greater likelihood of evident bodily injury as opposed to death or disabling injury. This variable accounts, along with the restraint system use indicator, for factors such as structural integrity of the vehicle and door failures on impact.

*As mentioned previously, no evident injury accidents include property damage only and possible injury where possible injury is typically a minor injury that is not evident at the scene of the accident.

*It must be noted that once speeds exceed the posted limit, speeding indicator 1 overrides speeding indicator 2 as the primary cause from a reporting perspective. Hence, speeding indicators 1 and 2 split the accident population into "above speed limit" and "below speed limit" sub-populations. This segmentation provides unique insights into the impacts of speeds because the effects of these two speed categories are quite different.

†The parameters for safe speed were specified initially for the evident injury and disabling injury/fatality alternatives simultaneously. By so doing, we constrain the β's to be the same for both alternatives. We removed this constraint and specified the β's separately for the alternatives. Relaxing the constraint allowed us to conclude the impact of safe speed with respect with evident injury was statistically different from that associated with disabling injury/fatality.

‡The statistically insignificant parameter for passenger restraint possibly indicates very high collinearity between driver and passenger restraint system use. In addition, when accident types such as rear-ends, angle and sideswipes are explicitly accounted for in the specification, rear-seat passenger injury is largely accounted for.

Variable: Gender of driver
Finding: Greater probability of disabling injury/fatality relative to no evident injury or evident injury if the accident involved all male drivers.
This finding suggests that male drivers may be inherently greater risk takers and that risk is compounded by the exposure factor in multi-vehicle collisions when all drivers are male.

Variable: Percentage of curve length per kilometer of roadway
Finding: Greater probability of evident injury or disabling injury/fatality than no evident injury
This finding is consistent with the earlier finding on the same variable in the no evident injury model (as shown in Table 2). The finding implies that curve-length percentage increases the likelihood of an injury on a roadway section by possibly affecting the driving task and driver behavior.

Variable: Number of horizontal curves per kilometer of roadway
Finding: Greater probability of no evident injury or disabling injury/fatality relative to evident injury
This variable illustrates that evident injury is a less likely consequence as the number of curves per kilometer increases. This may be because some drivers' natural reaction is to slow down when faced with many curves in close proximity, thus decreasing the likelihood of injury accidents.

Variable: Curve–sobriety interaction
Finding: Greater probability of disabling injury/fatality relative to no evident injury or evident injury
This variable captures the aggravating impact of curves on drunk driving. From a design perspective, this is an important finding because it presents opportunities for highway engineers to mitigate circumstances that aggravate drunk driving effects. A drunk driver's lack of control is particularly critical on horizontal curves resulting in lane violations and ensuing multi-vehicle collisions or severe run-off-the road impacts.

Variable: Snow-covered pavement indicators*
Finding: Greater probability of no evident injury relative to evident injury or disabling injury
This finding indicates the impact of seasonal† as well as location-specific effects on accident severity. The presence of snow on the pavement at the time of the accident may indicate a general caution observed by drivers. If an accident were still to occur, the greater caution exercised by drivers helps mitigate the severity of an accident by reducing the effect of aggravating factors such as speed. On the other hand, presence of snow may also capture the higher observed frequency of "parked vehicle" accidents (i.e. disabled vehicles or those vehicles parked to put chains on) which tend to be property damage only. Lane obliteration may cause lane violations and ensuing collisions such as sideswipe and same direction accidents which were observed to be milder in severity.

Variable: Vehicle-mass difference indicator
Finding: Greater probability of evident injury or disabling injury/fatality relative to no evident injury
This variable captures the effect of truck-passenger car collisions on accident severity in two-vehicle accidents. By isolating two-vehicle collisions, we truly capture vehicle-mass difference effects, as opposed to a combination of vehicle-mass and exposure-related effects that would be present in multivehicle collisions involving more than two vehicles.

Variable: Accident location indicators
Finding: Greater probability of evident injury or disabling injury/fatality relative to no evident injury if the accident occurred off the road
This variable captures the impacts of off the road accidents due to roadside features such as ditches and embankments. Such features tend to cause an injury. The findings indicate that the likelihood of evident injury is significantly greater than disabling injury/fatality in off-the-road collisions. Accounting explicitly in the specification for specific accident types such as overturns, which typically occur in off-the-road collisions, allows us to isolate the impact of the off-the-road coefficient for disabling injury/fatality severities.‡

Variable: Age–sobriety interaction
Finding: Greater likelihood of evident injury relative to disabling injury/fatality or no evident injury
This variable provides insight into an important two-way interaction that has not been investigated prior to this study. Age and sobriety have long been identified to play separate but significant roles in accident occurrences and severities. Several studies (Jonah 1986; Mayhew et al. 1986) have shown that

*As Table 3 shows, the β's for the evident injury and disabling injury/fatality categories were estimated unconstrained (i.e. separate coefficients for each severity category) and found to give statistically superior results relative to the constrained case (as measured by a likelihood ratio test).

†Seasonal effects capture, in addition to direct weather effects, factors such as traffic volume. Reduced traffic volumes during the months of November through March reduce the likelihood of multi-vehicle accidents. Indirectly, this accounts for exposure.

‡Off-the-road coefficients for evident injury and disabling injury/fatality were estimated separately. By doing so, the parameter for disabling injury/fatality was determined to be significantly lower than that for evident injury indicating that run-off-the-road by themselves are more likely to cause evident injury than disabling injury/fatality. It is in the presence of collisions such as vehicle overturns that the likelihood of disabling injury/fatality is enhanced.

older drivers are less prone to risk taking than younger drivers. Coupled with this, the risk of crash involvement of older drivers is also reduced due to greater driving experience. In addition, it has also been noted that alcohol-related impairment in driving is greater among older drivers. Given that an accident occurs, the combination of these factors results in injury accidents that are not as severe as disabling/fatality collisions. Being less likely to take risks and having greater driving experience seems to offset the greater impairment in driving that alcohol causes in older drivers, at least in terms of severity. However, the effect that such factors have on overall accident frequency is an open question that is not addressed in this study.

Variable: Night-time–pavement condition interaction
Finding: Greater likelihood of evident injury or disabling injury/fatality relative to no evident injury
This variable models the effect of night-time conditions and icy pavements on accident severities. In the event an accident occurred under such conditions, the positive coefficient of this variable with respect to evident injury and disabling injury/fatality indicates the influence of temperature-related and seasonal factors on driving. The importance of this interaction term stems from the compounding effect that night-time conditions have on driver behavior under icy conditions. It may be argued that the propensity of accidents occurring in icy weather could be lower during the night because of increased caution among drivers; however, given that an accident occurs, the severity is likely to be high. This higher severity may be in part caused by slower driver-reaction times which tend to be significantly slower at night.*

Variable: Fixed object–horizontal curve interaction
Finding: Greater probability of disabling injury/fatality relative to evident injury or no evident injury
This interaction term accounts for the impact of roadside features on accident severities on horizontal curves. The finding underscores the importance of roadside design on horizontal curves.

Variable: Fixed object–icy pavement interaction
Finding: Greater probability of no evident relative to evident injury or disabling injury/fatality
This variable further corroborates, as mentioned previously, the impact of speed on the severity of fixed object collisions. Icy weather acts as a deterrent to speeding, and as a result the consequence of fixed object collisions are likely to be less severe. Again, this finding does not relate to the frequency of such collisions which could be expected to be higher under such conditions.

In addition to examining the impact of key variables on accident severity, elasticities of important design variables were also examined. Elasticity is the measure of the percentage change in the probability of a specific severity level for a unit percentage change in an independent variable. It is generally computed as a point-measure for continuous variables.† An elasticity greater than unity in absolute value indicates that the dependent variable is elastic with respect to the subject independent variable. The elasticities of overall accident severity probability with respect to curve-length percentage and number of horizontal curves per kilometer of roadway were computed to be -0.2704 and -0.9017 respectively. Intuitively this says that a 1% increase in the percentage of horizontal curve length per kilometer will result in a 0.2704% increase in the likelihood of an accident being evident injury or disabling injury/fatality. Also, a 1% increase in the number of horizontal curves per kilometer will result in a 0.9017% increase in the probability of the accident resulting in no evident injury or disabling injury/fatality. While both elasticities are less than 1, the elasticity computation provides interesting insight into the comparative importance of these two variables in determining accident severity.

CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

The study provides a framework for estimating accident severity likelihood conditioned on the occurrence of an accident. It was concluded that a nested logit model which accounted for shared unobservables between property damage and possible injury accidents provided the best structural fit for the observed distribution of accident severities. This represents an important step in the methodological evaluation of ITS with respect to accident safety. By developing a probabilistic model that contains several important variables representing geometric, weather, and human factors we have shown that ambiguity and bias stemming from confounding effects in a partially specified model can be eliminated. In addition, this research

*The element of surprise and emergency response are important factors affecting driver reaction times. Several studies (Triggs and Harris 1982; Olson 1989; Hooper and McGee 1983; Taoka 1982) have evaluated driver reaction times under varying conditions and for different age groups, and concluded that night-time reaction times could be significantly higher than daytime values. The significance of the night-time–pavement interaction term presents a surrogate factor for reaction time, and illustrates the importance of potentially challenging highway geometrics.

†Elasticities over a larger range of independent variable values are misleading when computed using this formula. In addition, elasticities for indicator variables which have binary values of 0 or 1 are meaningless.

provides suggestive results by its use of variables such as curve–sobriety interaction and curve–pavement surface interaction. Specifically, it suggests that ITS may be an effective means of compensating for adverse design, human factors, and weather conditions. A well designed ITS could significantly improve the driving task in the presence of adverse factors such as alcohol, inclement weather, and complex roadway geometrics. A significant shift in the distribution of accident severities toward milder accidents in combination with lower accident frequencies (Shankar et al. 1995) will provide a basis for ITS evaluation. Further research which links the severity model to models of accident severity cost is needed to assess the potential and extent of savings in accident cost.

REFERENCES

Alassar, L. Analysis of heavy truck accident severity. J. Adv. Transportation 22: 77–91; 1988.

Ben-Akiva, M.; Lerman, S. R. Discrete choice analysis: Theory and application to travel demand. Cambridge, MA: MIT Press; 1985.

Evans, L. Double pair comparison—a new method to determine how occupant characteristics affect fatality risk in traffic crashes. Accid. Anal. Prev. 18: 217–228; 1986a.

Evans, L. The effectiveness of safety belts in preventing fatalities. Accid. Anal. Prev. 18: 229–241; 1986b.

Evans, L. The fraction of traffic fatalities attributable to alcohol. Accid. Anal. Prev. 22: 587–602; 1990.

Glimm, J.; Fenton, R. E. An accident-severity analysis of a uniform-spacing headway policy. IEEE Trans. Vehicular Technol. VT-29(1): 96–103; 1980.

Golob, T. F.; Recker, W. W.; Leonard, J. D. An analysis of the severity and incident duration of truck-involved freeway accidents. Accid. Anal. Prev. 19: 375–395; 1987.

Holubowycz, O. T.; Kloeden, C. N.; McLean, J. A. Age, sex, and blood alcohol concentration of killed and injured drivers, riders, and passengers. Accid. Anal. Prev. 26: 483–492; 1994.

Hooper, K.; McGee, H. Driver perception-reaction time: Are revisions to current specification values in order?. Transportation Res. Rec. 904: 21–30; 1983.

Hutchinson, T. P. Statistical modelling of injury severity, with special reference to driver and front seat passenger in single-vehicle crashes. Accid. Anal. Prev. 18: 157–167; 1986.

Jonah, B. S. Accident risk and risk-taking behaviour among young drivers. Accid. Anal. Prev. 18: 255–271; 1986.

Jones, I. S.; Whitfield, R. A. Predicting injury risk with "new car assessment program" crashworthiness ratings. Accid. Anal. Prev. 20: 411–419; 1988.

Lassarre, S. The introduction of the variables "traffic volume," "speed" and "belt-wearing" into a predictive model of the severity of accidents. Accid. Anal. Prev. 18: 129–134; 1986.

Lui, K. J.; McGee, D.; Rhodes, P.; Pollock, D. An application of a conditional logistic regression to study the effects of safety belts, principal impact points, and car weights on drivers' fatalities. J. Safety Res. 19: 197–203; 1988.

Mannering, F.; Winston, C. Dynamic empirical analysis of household vehicle ownership and utilization. Rand J. Econ. 16(2): 215–236; 1985.

Mannering, F.; Winston, C. Brand loyalty and the decline of American automobile firms. Brookings Papers on Economic Activity. Microeconomics 67–114; 1991.

Mannering, F.; Winston, C. Automobile air bags in the 1990's: Market failure or market efficiency? J. Law Econ. 38: 265–279; 1995.

Massie, D. L.; Campbell, K. L.; Blower, D. F. Development of a collision typology for evaluation of collision avoidance strategies. Accid. Anal. Prev. 25: 241–257; 1993.

Mayhew, D. R.; Donelson, A. C.; Beirness, D. J.; Simpson, H. M. Youth, alcohol and relative risk of crash involvement. Accid. Anal. Prev. 18: 273–287; 1986.

McFadden, D. Econometric model of probabilistic choice. In Structural analysis of discrete data with econometric applications, Manski, McFadden, (Eds). Cambridge, MA: MIT Press; 1981.

Mercer, W. G. Influences of passenger vehicle casualty accident frequency and severity: unemployment, driver gender, driver age, and drinking driving and restraint device use. Accid. Anal. Prev. 19: 231–236; 1987.

Olson, P. L. Driver perception response time. SAE Paper No. 890731:67–77; 1989.

Press, S. J.; Wilson, S. Choosing between logistic regression and discriminant analysis. J. Am. Stat. Assoc. 73: 699–705; 1978.

Shankar, V. N.; Mannering, F. L.; Barfield, W. Effect of roadway geometrics and environmental conditions on rural accident frequencies. Accid. Anal. Prev. 27: 371–389; 1995.

Shao, S. P. Estimating car driver injury severity in car/tractor–trailer collisions. Accid. Anal. Prev. 19: 207–217; 1987.

Shibata, A.; Fukuda, K. Risk factors of fatality in motor vehicle traffic accidents. Accid. Anal. Prev. 26: 391–397; 1994.

Small, K. A.; Hsiao, C. Multinomial logit specification tests. Int. Econ. Rev. 26: 619–627; 1985.

Taoka, G. T. Statistical evaluation of brake reaction time. Compendium Of Technical Papers. 52nd Annual Meeting of Institute of Transportation Engineers; 1982: 30–36.

Train, K. Qualitative choice analysis: theory, econometrics, and application to automobile demand. Cambridge, MA: MIT Press; 1986.

Triggs, T.; Harris, W. G. Reaction time of drivers to road stimuli. Human Factors Report HFR-12, Monash University, Australia; 1982.