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The effect of ice warning signs on ice-accident frequencies and severities

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Abstract

Signing of non-permanent road surface conditions, such as ice, is difficult because hazard formation, location, and duration are unpredictable. Subsequently, many state transportation departments have begun to question the sensibility of expending material and personnel resources to maintain ice warning signs when little proof exists of their effectiveness in improving highway safety. This research statistically studies the effectiveness of ice warning signs in reducing accident frequency and accident severity in Washington State. Our findings show that the presence of ice warning signs was not a significant factor in reducing ice-accident frequency or ice-accident severity. However, we were able to identify significant spatial, temporal, traffic, roadway and accident characteristics that influenced ice-accident frequency and severity. The identification of these characteristics will allow for better placement of ice warning signs and improvements in roadway and roadside design that can reduce the frequency and severity of ice-related accidents.

Keywords: Ice warning signs; Ice-accident frequencies; Roadway and roadside design

1. Introduction

The unpredictable nature of ice formation, location, and duration on roadway surfaces makes effective signing difficult. Still, state transportation departments have invested millions in the placement and maintenance of state ice-warning signs (the standard diamond-shaped with yellow background and black legend) with little or no evidence of their effectiveness in reducing the frequency or severity of accidents.

Conceptually, to effectively place ice-warning signs one must establish the probability of ice forming along particular route segments. Ice formation is a complex process that is both location and time dependent. Ice can form over vast stretches of roadway or in localized areas such as bridges or shaded areas and can persist for hours or days. Historical climatic data, including minimum temperature, precipitation, snowfall, freezing elevations, hours of sunshine, and dew point provide macroscopic information that is of minimal use in the prediction of localized icing. A system of on-road sensors offers promise for the accurate prediction of localized icing, but expense and reliability issues are barriers to implementation.

Many confounding effects are present in ice-related accidents. Vehicle-related factors such as speed, tire traction, braking system, and weight all influence the probability of an accident occurring. Driver reaction further confounds the problem of accurately quantifying the probability of ice-related accident occurrence. If drivers heed warning signs and decelerate, the probability of having an accident is decreased, but whether or not drivers react properly to ice-warning signs, under icy conditions, is an open question.

Our survey of states indicated that only Connecticut, Delaware, Florida, Hawaii, Iowa, Kansas, Massachusetts, Missouri, and Rhode Island do not use ice-warning signs (Carson, 1998). Given that these states are in both warm and cold regions, the use of ice warning signs is clearly not entirely dictated by climate. In terms of sign placement for those states using ice-warning

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signs, our survey shows that states have compensated for the difficulties in predicting ice as a roadway hazard by resorting to over signing, and/or standardized sign placement (placing signs on all bridges, regional boundaries; or other standard roadway features). Both of these policies seem to be intended to protect state transportation agencies from liability as much as they are intended to improve highway safety, and both have potentially significant effects on driver behavior. Too many signs or ice-warning signs posted at potentially inappropriate locations (i.e. locations where the ice hazard is rarely present) can desensitize drivers thereby negating any safety enhancement the signs may have.

In Washington State, as in other states that use ice-warning signs, there is considerable variation from one maintenance area to another (Washington State is divided into 24 maintenance areas). All but one of Washington's 24 maintenance areas uses ice-warning signs. In that maintenance area, ice-warning signs were permanently removed in the spring of 1994 because they were deemed ineffective in improving highway safety. Some areas in Washington use ice warning signs sparingly (i.e. sign placement sites are identified on the basis of accident histories) and others place ice warning signs frequently using jurisdictional or geographic boundaries, engineering or maintenance personnel judgment, requests from the motoring public, or roadway features (i.e. bridges, junctions) as a basis. As is the case nationally, little statistical evidence is available to show the effectiveness of ice-warning signs or provide guidance on the placement of ice warning signs.

The intent of this paper is to statistically evaluate the effectiveness of ice-warning signs in Washington State and to provide guidance for effective sign placement. To do this we collected data from accident records and used statistical models to estimate the frequency and severity of ice accidents. Given the wide variability in sign-placement practices, even within a state, we do not expect to find a strong statistical relation between the presence of signs and a reduction in the frequency and/or severity of accidents. However, we do expect our analysis of accident data to reveal valuable information on roadway characteristics that affect highway safety when ice is present and, when combined with ongoing improvements in the ability to predict ice formation (from roadway sensors, etc.), this information can provide some basis for the effective placement of ice-warning signs in the future.

2. Methodological approach

We evaluate the effectiveness of ice warning signs in Washington State by analyzing all state accident data involving ice and consider the frequency of ice-related accidents on roadway sections (defined by changes in roadway geometrics as will be discussed later) and the severity of ice-related accidents.

Statistical modeling of ice-related accident frequency on roadway sections is a classic count-data problem. In terms of accident frequency analysis, much of the work performed to date has attempted to relate various roadway, environmental, traffic, driver and/or safety mitigation measures to the number of accidents occurring on a section of roadway in some time period (Jovanis and Chang, 1986; Wong and Nicholson, 1992; Miaou and Lum, 1993; Poch and Mannering, 1996; NCHRP, 1997; Milton and Mannering, 1998). In studies more closely related to ice-warnings, a number of researchers have attempted to relate accident frequency to adverse weather conditions, predominantly rain or snow (Brodsky and Hakkert, 1988; Shankar et al., 1995). Hanbali (1992) investigated the effects of winter road maintenance (i.e. snowplowing, deicing applications, etc.) on accident frequencies but the effects of ice warning signs were not incorporated into his investigation. In fact, no significant literature was uncovered that investigated the effect of ice-warning signs on accident frequency.

Methodologically, attempts to analyze accident frequency data have ranged from the use of conventional multiple linear regression using least squares regression techniques to methods involving other distributions including Poisson and negative binomial (Hammerslag et al., 1982; Senn and Collie, 1988; Joshua and Garber, 1990; Maher, 1991). More recently, the use of zero-inflated Poisson and negative binomial models has been explored (Shankar et al., 1997). Conventional linear regression has been shown to be inappropriate for modeling accident count data because the model form is not restrained from predicting negative values and the near certain presence of heteroscedasticity (equation disturbance terms with unequal variance — a violation of regression assumptions) results in inefficient coefficient estimates (i.e. estimates that do not have minimum variance — see Washington et al., 2000).

In light of the problems associated with linear regression, many researchers have used Poisson regression as a means to better predict accident frequency. The Poisson regression model is:

$$P(Y_i) = \frac{e^{(-\lambda_i)}(\lambda_i^{Y_i})}{Y_i!} \tag{1}$$

where $P(Y_i)$ is the probability of Y_i accidents occurring on roadway section i in some predetermined time period, and λ_i is the Poisson parameter which is equal to the expected value of $Y_i(E[Y_i])$. Covariates are introduced in the Poisson model as

$$\lambda_i = \exp(\boldsymbol{\beta} \boldsymbol{X}_i) \tag{2}$$

where λ_i, is the Poisson parameter, $\boldsymbol{\beta}$ is a vector of estimable coefficients, and $\boldsymbol{X}_i$ is a vector of covariates determining the frequency of accidents on roadway section i. The vector $\boldsymbol{\beta}$ is estimated using standard maximum likelihood methods.

One important property of the Poisson model is that it restricts the mean and variance of the distribution to be equal ($E[Y_i] = \mathrm{Var}[Y_i]$). If this equality does not hold, the data are said to be either underdispersed ($E[Y_i] > \mathrm{Var}[Y_i]$) or overdispersed ($E[Y_i] < \mathrm{Var}[Y_i]$). If the Poisson's mean/variance equality is violated, the resulting coefficient estimates will be biased.

In modeling accident frequency data, it has been shown that overdispersion is a persistent problem (Miaou and Lum, 1993; Shankar et al., 1995; Poch and Mannering, 1996). The negative binomial model is appropriate for overdispersed data because the model relaxes the constraint of equal mean and variance. This relaxation of the Poisson constraint is accomplished through the addition of a Gamma-distributed error term to the Poisson model such that (see Eq. (2))

$$\log \lambda_i = \boldsymbol{\beta} \boldsymbol{X}_i + \xi_i \tag{3}$$

where ξ_i is the Gamma-distributed error term and all variables are as previously defined. The addition of ξ_i allows the mean to differ from the variance such that

$$\mathrm{Var}[Y_i] = E[Y_i][1 + \alpha E[Y_I]] \tag{4}$$

where a is an additional estimable coefficient. If α is not significantly different from zero, the data are not overdispersed, and the Poisson regression is appropriate.

Recent work by Shankar et al. (1997) suggests that simple Poisson and negative binomial modeling efforts do not address the possibility that some roadway sections observed to have no accidents during a specified time period may be qualitatively different from Poisson or negative binomial distributed accident frequency counts. They suggest that two processes may be simultaneously at work in such situations (i.e. a dual-state system). The zero count state (i.e. having no accidents observed in some time period) may be the cumulative effect of whether an accident is ever to occur (i.e. the roadway is virtually safe) as well as the possibility of zero accidents arising from the underlying count distribution (i.e. the roadway is unsafe but, by chance, no accidents were observed in the observation period). Hence, cumulatively, one process may determine if any accident will ever occur and the other determines the Poisson or negative binomial distribution that describes the distribution of accident frequencies. The statistical consequences of estimating a dual-state system as a single-state system (i.e. ignoring the possibility of inherently safe highway sections) can lead to erroneous inferences regarding overdispersion in the data and underlying causality.

Dual-state systems are estimated using zero-inflated models. Both zero-inflated Poisson (ZIP) and negative binomial (ZINB) models assume that two different processes are at work for zero count data and non-zero count data. The zero-inflated Poisson model is specified by letting $Y_i = 0$ with probability q_i, and Y_i be a Poisson distribution with probability $1 - q_i$. The probability of the zero count event and the non-zero count event is then

$$P[Y_i = 0] = q_i + [1 - q_i]R_i(0) \tag{5}$$

$$P[Y_i = y_i > 0] = [1 - q_i]R_i(y_i) \tag{6}$$

Where $R_i(y_i) = e^{-\lambda_i}\lambda_i^{y_i}/y_i!$ and $\lambda_i = \exp(\boldsymbol{\beta}\boldsymbol{X}_i)$ where all variables are as previously defined. Similarly, the zero-inflated negative binomial model can be derived with,

$$R_i(y_i) = \frac{\Gamma(\theta + y_i)}{[y_i!\Gamma(\theta)]u_i^{\theta}[1 - u_i]y_i} \tag{7}$$

with $\theta = 1/\alpha$ (where a is the dispersion parameter) and $u_i = \theta/(\theta + \lambda_i)$, Coefficient estimation for the zero-inflated Poisson and negative binomial models is conducted using standard maximum likelihood procedures.

Selection of an appropriate count model (Poisson, zero-inflated Poisson, negative binomial, or zero-inflated negative binomial) can be empirically established by evaluating the t-statistic of the dispersion coefficient (α in Eq. (4)) and Vuong's test for zero-inflation (which will determine the appropriateness of zero-inflated models-either Poisson or negative binomial). The Vuong test (Vuong, 1989) is a t-statistic-based test computed as

$$V = \frac{\bar{m}\sqrt{N}}{S_m} \tag{8}$$

where $\bar{m}$ is the mean with $m = \log[f_1(.)/f_2(.)]$, (with $f_1(.)$ being the density function of the ZINB distribution and $f_2(.)$ is the density function of the normal (not zero inflated) negative binomial distribution), and S_m and N are the standard deviation of m and sample size, respectively. A value greater than 1.96 (the 95% confidence level for the t-test) for V favors the ZINB while a value less than -1.96 favors the normal negative binomial distribution (values between 1.96 and -1.96 mean that the test is inconclusive). The same procedure holds for comparing ZIP with normal Poisson. To carry out the test, both the parent (Poisson or negative binomial) and zero-inflated distribution need to be estimated and tested using a t-statistic.

Contrary to accident frequency data, accident severity data (the most severe consequence being a fatality, injury, or property damage only) are discrete and not count data. In such cases, a multinomial logit modeling structure is appropriate (Shankar and Mannering, 1996). In applying the multinomial logit structure, we seek to determine the likelihood of various severity types occurring given that an accident has happened. Let $P_n(i)$, be the probability of accident n being of

Table 1
Ice-accident frequency zero-inflated negative binomial model results for Interstates

Independent variable	Estimated coefficient	t-statistic
Non-zero accident state as a negative binomial		
Constant	0.236	0.43
Spatial characteristics		
Northwest region indicator (1 if roadway section was in WSDOTs Northwest region, 0 otherwise)	−0.315	−4.36
South Central region indicator (1 if roadway section was in WSDOTs South Central region, 0 otherwise)	0.799	11.47
Eastern region indicator (1 if roadway section was in WSDOTs Eastern region, 0 otherwise)	0.319	3.42
Urban indicator (1 if roadway section was in an urban area, 0 otherwise)	−0.00036	−2.77
Temporal characteristics		
1994 indicator (1 if accident data were from 1994, 0 otherwise)	−0.147	−2.35
Traffic characteristics		
Single unit truck percentage of average annual daily traffic	−0.074	−3.07
Roadway characteristics		
Posted speed limit in (km/h)	−0.0241	−4.84
Section length (in km)	1.15	10.55
Number of lanes in the opposing direction	0.328	7.80
Left shoulder width (in m)	−0.252	−11.98
Grade indicator (1 if the roadway section is on an upward grade, 0 otherwise)	−0.208	−4.44
Straight section indicator (1 if roadway Section has no horizontal curves, 0 otherwise)	0.419	4.11
Horizontal curve radius (horizontal curve radius in meters if a horizontal curve is present in the roadway section, 0 otherwise)	−0.000072	−4.39
Dispersion parameter α	1.66	13.31
Zero accident state		
Constant	2.3654	5.10
Spatial characteristics		
Eastern region indicator (1 if roadway section was in WSDOTs Eastern region, 0 otherwise)	−0.60033	−3.29
Temporal characteristics		
1994 indicator (1 if accident data were from 1994, 0 otherwise)	0.22960	2.57
Roadway characteristics		
Posted speed limit (in km/h)	−0.0197	−4.20
Section length (in km)	−8.68	−9.61
Straight section indicator (1 if roadway section has no horizontal curves, 0 otherwise)	0.344	2.58
Number of observations	23 427	
Restricted log likelihood	8606.20	
Log likelihood at convergence	7811.51	
Vuong statistic	10.18	

severity i and let S_{in} be a linear function that determines the severity of the accident such that

$$S_{in} = \boldsymbol{\beta}_i \boldsymbol{X}_n + \varepsilon_{\mathrm{in}} \tag{9}$$

where β_i is a vector of estimable parameters, X_n is a vector of the observable characteristics that determine severity and ε_{in} is an unobservable random error. The probability that accident n is of severity i can be expressed as the probability that S_{in} is greater than all other S_{in}, or

$$P_n(i) = P(S_{in} > S_{\mathrm{I}n}) \forall \mathrm{I} \neq i \tag{10}$$

By substituting the Eq. (9) into Eq. (10), the latter can be written as

$$P_n(i) = P(\boldsymbol{\beta}_i \boldsymbol{X}_n + \varepsilon_{in} > \boldsymbol{\beta}_{\mathrm{I}} \boldsymbol{X}_n + \varepsilon_{In}) \forall \mathrm{I} \neq I \tag{11}$$

An estimable model can be developed by assuming a distribution of the random error term, ε. If a normal distribution were assumed for these terms, a probit model would result. However, models of this type are computationally impractical in a situation with more than two discrete outcomes. An alternate approach is to assume that the error terms are generalized extreme value (GEV) distributed. Based on the GEV assumption, the multinomial logit model can be derived as (McFadden, 1981),

$$P_n(i) = \frac{\exp[\boldsymbol{\beta}_i \boldsymbol{X}_n]}{\sum_{\mathrm{I}} \exp[\boldsymbol{\beta}_{\mathrm{I}} \boldsymbol{X}_n]} \tag{12}$$

where all terms are as previously defined. Given this equation, the coefficient values in the vector $\boldsymbol{\beta}$ can be estimated using standard maximum likelihood methods.

Table 2
Ice-accident frequency negative binomial model results for principal arterial State highways

Independent variable	Estimated coefficient	t-statistic
Constant	−3.4954	−17.02
Spatial characteristics		
Northwest region indicator (1 if roadway section was in WSDOTs Northwest region, 0 otherwise)	−0.594	−10.82
South Central region indicator (1 if roadway section was in WSDOTs South Central region, 0 otherwise)	−0.635	−8.48
Temporal characteristics		
1994 indicator (1 if accident data were from 1994, 0 otherwise)	−0.108	−2.76
Traffic characteristics		
High average annual daily traffic per lane indicator (1 if AADT per lane is greater than 20 000 vehicles, 0 otherwise)	1.356	18.27
Average annual daily traffic per lane divided by/section length (in m)	−6.22	−9.06
Total truck percentage in average annual daily traffic	−0.0148	−3.85
Roadway characteristics		
High posted speed limit indicator (1 if the speed limit exceeds 80 km/h, 0 otherwise)	0.567	11.70
Section length (in km)	1.72	16.16
Total number of lanes (both directions)	0.245	11.14
Narrow right shoulder width indicator (1 if the right shoulder is less than 1.2 m, 0 otherwise)	−0.211	−4.79
Grade indicator (1 if the roadway section is on an upward grade, 0 otherwise)	−0.027	−4.39
Straight section indicator (1 if roadway section has no horizontal curves, 0 otherwise)	0.215	4.61
Horizontal curve length (in m)	0.00029	21.82
Horizontal curve central angle (in °)	−0.00099	−3.93
Dispersion parameter α	7.00	23.57
Number of observations	94 205	
Restricted log likelihood	−15764.83	
Log likelihood at convergence	−14631.42	

3. Data

For both aspects of this investigation (i.e. ice-accident frequency and severity), accident information and related characteristics were gathered from the Washington State Department of Transportation (WSDOT) accident database. From January 1993 to December 1995, 8176 accidents involving ice were reported in Washington.

Current ice warning sign locations were identified using WSDOTs computerized sign inventory. This information was supplemented through an area maintenance survey to ensure accuracy. Ice warning sign presence was denoted in the data set with an indicator variable, 1 if present, 0 if not. Care was taken to ensure that if the ice warning sign indicator variable was set as 1, there was in fact a sign erected at the time of the accident(s) (many signs are erected and removed seasonally) and that it was directianally consistent with the reported accident(s). Large discrepancies in both the number of ice warning signs and their exact locations were discovered through this process indicating a need for an improved sign inventory and record keeping system.

To investigate the effect of ice warning signs on ice-accident frequency, the accident data were supplemented with roadway geometric and traffic data from other WSDOT databases and computerized state roadway inventory files were used as a source of traffic volume, truck percentage, peak hour factor, geometric and speed data. In cases where a section of highway contained curbs or walls, an indicator variable was used for identification because no shoulder width data was available. Vertical curves were identified by grade and angle or inflection point. Length, radius, central angle, horizontal curve type, and the direction of curvature identified horizontal curves.

Roadways were divided into homogeneous sections of various lengths. Section limits were defined by changes to any geometric or traffic-related characteristic (e.g. a new section would be identified when the shoulder width, number of lanes, state route number, vertical or horizontal curve characteristics, and similar geometric features changed). In addition, sections were defined where changes in speed, average annual daily traffic, truck percentage or peak hour factor occurred. Ice-accident frequencies and ice warning sign presence (allowing for motorist sight distance upstream of the sign and accident-involved vehicle travel beyond the sign) were determined for each homogeneous roadway section.

In the case of ice-accident frequency, the ice warning sign indicator variable (1 if an ice warning sign was in place, 0 otherwise) can not be used directly because of possible endogeneity. That is, ice-accident frequency can potentially affect the probability of an ice-warning sign being present since one of the standard practices is to place ice-warning signs in response to the frequency of ice-related accidents. If this endogeneity is ignored, one might arrive at the erroneous finding that ice-warning signs increase accident frequency because they are placed at locations with a history of ice-related accidents. To account for this endogeneity, we used an -instrumental variables approach. Using the ice warning sign indicator variable as the dependent variable, a binary logit model was estimated to predict the probability of a sign being present using only exogenous independent variables (spatial, temporal, traffic and roadway characteristics). This logit-predicted probability was used in place of the ice warning sign indicator variable when estimating the ice-related accident frequency models.

Table 3
Ice-accident frequency negative binomial model results for minor arterial State highways

Independent variable	Estimated coefficient	t-statistic
Constant	−4.50	−11.03
Spatial characteristics		
Olympic region indicator (1 if roadway section was in WSDOTs Olympic region, 0 otherwise)	0.321	3.69
Southwest region indicator (1 if roadway section was in WSDOTs Southwest region, 0 otherwise)	0.544	4.53
Eastern region indicator (1 if roadway section was in WSDOTs Eastern region, 0 otherwise)	−0.985	−3.71
Traffic characteristics		
Average annual daily traffic per lane	0.000027	3.57
Peak hour percentage of average annual daily traffic	−0.059	−2.37
Roadway characteristics		
Posted speed limit (in km/h)	0.0074	2.31
Section length (in km)	1.50	7.44
Narrow right shoulder width indicator (1 if the right shoulder is less than 1.2 in, 0 otherwise)	−0.168	−2.31
Median indicator (1 if median is present, 0 otherwise)	0.614	2.61
Horizontal curve length (in m)	0.000224	2.75
Dispersion parameter α	12.47	14.19
Number of observations	60 482	
Restricted log likelihood	−5254.91	
Log likelihood at convergence	−4986.66	

For accident severity modeling, which looks at the severity of an accident once an accident has occurred, detailed data from the accident report are used (i.e. the exact location of the accident, time of day, number of vehicles involved, etc.) along with the more general roadway information used in accident frequency modeling. Three severity outcomes are considered: fatality; injury (possible, evident, or disabling); or property damage only, defined as the most severe consequence of the accident. In the accident severity case, the presence of an ice-warning sign is not endogenous because it is unlikely that individual accident characteristics will determine sign placement and our statistical analysis showed this to be the case[1].

4. Estimation results: ice-accident frequency models

To asses the effect of ice-warning signs on accident frequencies, three separate frequency models were estimated to better account for differences attributable to roadway functional classes of interstate, principal arterial, and minor arterial (the use of separate models was statistically validated, Carson 1998).

For interstate ice-accident frequencies the zero-inflated negative binomial model was deemed most appropriate. The data exhibited overdispersion (α was highly significant with a t-statistic of 13.31) indicating the appropriateness of the negative binomial model over the Poisson model. Further, zero-inflation was confirmed through Vuong's test for zero-inflation ($V=$ 10.18). Model estimation results are shown in Table 1.

The presence of ice-warning signs was found not to significantly affect ice-accident frequency. For the non-zero accident state, noted differences were found among the various WSDOT regions with respect to ice-accident frequency. Seasonal, climatic and topographic variations among the locales likely explain these differences (i.e. the South Central and Eastern regions experience a greater frequency of freezing temperatures and icing conditions). Ice-accident frequency was found to be lower along urban interstates. Lower congestion-related travel speeds and highway maintenance practices may explain this. For the zero-accident state, roadway sections in WSDOTs Eastern region was found to be less likely to be in the zero-accident state and this again could be an artifact of the more severe climate in the eastern portion of the state.

In terms of temporal characteristics, accidents occurring in 1994 were less likely in the non-zero state and more likely in the zero-accident state as indicated by the negative and positive signs respectively (this indi-

[1] It is standard practice to place ice-warning signs in response to the frequency of ice related accidents but not to the severity of these accidents.

Table 4
Ice-accident severity logit model results for Interstates

Independent variable	Estimated coefficient	t-statistic
Constant 1 (defined for property damage only severity level)	3.32	7.14
Constant 2 (defined for injury severity level)	2.82	6.21
Spatial characteristics		
Resident location indicator (1 if accident occurred within 24 km of residence, 0 otherwise; defined. for fatality severity level)	−2.25	−2.93
Olympic region indicator (1 if accident occurred within WSDOTs Olympic region, 0 otherwise, defined for fatality severity level)	1.348	2.39
South Central indicator (1 if accident occurred within WSDOTs South Central region, 0 otherwise; defined for proper damage only severity level)	0.223	2.21
Temporal characteristics		
Thursday indicator (1 if accident occurred on a Thursday, 0 otherwise; defined for injury severity level)	0.278	2.20
Accident characteristics		
Truck tractor/semi-trailer indicator (1 if accident involved a truck tractor/semi-trailer, 0 otherwise; defined for severity level)	1.98	2.44
Alcohol impaired indicator (1 if accident involved an alcohol impaired driver, 0 otherwise; defined for injury severity level)	1.48	5.08
No alcohol indicator 1 (1 if accident did not involve an alcohol impaired driver, 0 otherwise; defined for fatality severity level)	−1.19	−2.22
No alcohol indicator 2 (1 if accident did not involve an alcohol impaired driver, 0 otherwise; defined for injury severity level)	0.384	3.76
Average driver age (the average age in years of all drivers involved in the accident; defined for property damage only severity level)	0.00077	3.32
Number of observations	2729.00	
Log likelihood at zero	−2998.11	
Log likelihood at convergence	−1856.98	
Percent correctly predicted	61.96	

cates that accident occurrence in 1994 was significantly lower than in other years). The mild temperatures that marked 1994 (an El Nino year) are one possible explanation for this finding. Also, for the non-zero accident state, ice-accident frequency was found to decrease as the percent of single unit trucks in the traffic stream increases[2]. This could relate to the reduction in speed that such vehicles have on the traffic stream.

Several roadway geometric characteristics were found to significantly affect ice-accident frequency along interstates for both the non-zero and zero accident states. For the non-zero accident state, ice-accident frequency was found to decrease as horizontal curve radius, left shoulder width and posted speed increased and on upward grades. The decrease in accident frequency as a result of higher posted speeds likely reflects the fact that hazardous roadway sections were more likely to have lower posted speeds and safer roadway section are more likely to have higher posted speeds.

On straight sections of interstate (i.e. no horizontal curves), ice-accident frequency was found to be higher. This may be an artifact of driver behavior (becoming complacent when not faced with geometric changes) or greater accident exposure along straight sections of interstate. Also, ice-accident frequency was found to increase as the number of opposing lanes increases and as the section length increases.

Roadway sections were found to be less likely to be in the zero-accident state as the posted speed limit and section length increased and more likely to be in the zero-accident state in straight sections. These results underscore the complex interaction between zero and non-zero accident states.

For principal arterials the model form deemed most appropriate for ice-accident frequency was the negative binomial model. The data exhibited overdispersion (α was highly significant with a t-statistic of 23.571) indicating the appropriateness of the negative binomial model over the Poisson model. Zero-inflation was not confirmed ($V < |1.96|$) indicating the appropriateness of the negative binomial model over the zero-inflated negative binomial model. Model results are shown in Table 2. As was the case for interstates, the presence of ice-warning signs was not a significant factor in ice-ac-

[2] It is noteworthy that average annual daily traffic (AADT) was not found to be a significant factor in determining accident frequency. This could be because many other variables included in the model are correlated with AADT making the effect of AADT on accident frequency one of second-order correlation.

cident frequency. Other findings shown in Table 2 serve to illustrate the diversity of factors influencing ice-accident frequency as well as the difference in roadway functional classification.

Finally, for accident frequencies on minor arterial state highways, the model form deemed most appropriate, as with principal arterial state highways, was the negative binomial model. The data exhibited overdispersion (a was highly significant with a t-statistic of 14.193) indicating the appropriateness of the negative binomial model over the Poisson model. Zero-inflation was not confirmed ($V < |1.96|$) indicating the appropriateness of the negative binomial model over the zero-inflated negative binomial model. Model results are shown in Table 3. As with interstates and principal arterials, the presence of ice-warning signs was found not to significantly affect ice-accident frequency.

5. Estimation results: ice-accident severity models

To evaluate whether ice-warning signs affected ice-accident severity we estimate three separate severity models, one for each of the roadway functional classes of interstate, principal arterial, and minor arterial. Again, the three accident severity outcomes considered are: fatality; injury (possible, evident, disabling); and property damage only and they refer to the most severe consequence of the accident.

The estimation results for accident severities on interstates are presented in Table 4. As was the case in the frequency models, the presence of ice-warning signs did not have a statistically significant effect on accident severity. Other findings indicate that ice-related accidents involving residents living within 24 km of the crash site are less likely to result in a fatality. Accidents occurring in WSDOTs Olympic region are more likely to result in a fatality, while accidents occurring in WSDOTs South Central region were more likely to

Table 5
Ice-accident severity logit model results for principal arterial State highways

Independent variable	Estimated coefficient	t-statistic
Constant 1 (defined for property damage only severity level)	4.45	8.54
Constant 2 (defined for injury severity level)	2.94	5.64
Spatial characteristics		
Resident location indicator 1 (1 if accident occurred within 24 km of residence, 0 otherwise; defined for fatality severity level)	−1.03	−2.17
Resident location indicator 2 (1 if accident occurred within 24 km of residence, 0 otherwise; defined for injury severity level)	0.352	2.92
Resident location indicator 3 (1 if accident occurred more than 24 km from residence, 0 otherwise; defined for injury severity level)	0.431	3.37
Olympic region indicator (1 if accident occurred within WSDOTs Olympic region, 0 otherwise, defined for injury severity level)	0.198	2.36
State Route 503 indicator (1 if accident occurred on State Route 503, 0 otherwise; defined for injury severity level)	−1.42	−2.27
Temporal characteristics		
1994 indicator (1 if accident data were from 1994, 0 otherwise)	0.175	2.36
Accident characteristics		
Number of vehicles involved in accident (defined for fatality severity level)	0.624	3.05
Number of vehicles involved in accident (defined for injury severity level)	0.246	4.61
Fuel spill indicator (1 if the accident involved a fuel spill, 0 otherwise; defined for fatality severity level)	3.07	3.73
Vehicle crosses centerline indicator (1 if accident involved a vehicle crossing the centerline, 0 otherwise; defined for injury severity level)	0.263	2.93
Alcohol impaired indicator (1 if accident involved an alcohol impaired driver, 0 otherwise; defined for injury severity level)	1.061	4.32
No alcohol indicator 1 (1 if accident did not involve an alcohol impaired driver, 0 otherwise; defined for fatality severity level)	−1.22	−2.66
No alcohol indicator 2 (1 if accident did not involve an alcohol impaired driver, 0 otherwise; defined for injury severity level)	0.416	4.76
Average driver age (the average age in years of all drivers involved in the accident; defined for property damage only severity level)	0.00426	2.09
Number of observations	3703	
Log likelihood at zero	−4068.16	
Log likelihood at convergence	−2500.25	
Percent correctly predicted	63.24	

Table 6
Ice-accident severity logit model results for minor arterial State highways

Independent variable	Estimated coefficient	t-statistic
Constant 1 (defined for property damage only severity level)	8.31	5.21
Constant 2 (defined for injury severity level)	7.04	4.35
Spatial characteristics		
Olympic Region indicator (1 if accident occurred within WSDOTs Olympic region, 0 otherwise; defined for fatality severity level)	2.90	2.30
Southwest indicator (1 if accident occurred within WSDOTs Southwest region, 0 otherwise; defined for injury severity level)	−0.665	−2.74
State Route 6 indicator (1 if accident occurred on State Route 6, 0 otherwise; defined for fatality severity level)	3.60	2.53
State Route 7 indicator (1 if accident occurred on State Route 7, 0 otherwise; defined for fatality severity level)	2.77	2.08
State Route 161 indicator (1 if accident occurred on State Route 161, 0 otherwise; defined for injury severity level)	0.752	2.33
Temporal characteristics		
February indicator (1 if accident occurred in February, 0 otherwise; defined for fatality severity level)	2.34	2.09
Accident characteristics		
Passenger car indicator (1 if all vehicles involved in the accident were passenger cars, 0 otherwise; defined for injury severity level)	0.907	2.93
Truck indicator 1 (1 if the accident involved a truck weighing less than 45 kN, 0 otherwise; defined for injury severity level)	0.708	2.32
Truck indicator 2 (1 if the accident involved a truck weighing more than 45 kN, 0 otherwise; defined for injury severity level)	2.81	2.41
Number of observations	1122	
Log likelihood at zero	−1232.64	
Log likelihood at convergence	−741.76	
Percent correctly predicted	63.81	

result in property damage only. These findings may be picking up different driving behavior in different regions of the State or unobserved climatic differences. We also found that ice accidents are more likely to result in injury if occurring on Thursday rather than on other days of the week. This could be an artifact of the data relating to climatic conditions and/or other unobserved effects that occurred on Thursdays in our database.

Truck tractors and semi-trailers were found to be more likely to result in a fatality. Accidents involving alcohol-impaired motorists were more likely to result in an injury, as were accidents involving motorists that had not been drinking (but to a lesser extent as indicated by the relative magnitudes of the coefficient estimates for these two variables). Non-drinking motorist-involved accidents, however, were also less likely to result in fatality. Finally, our findings show that as average driver age increases, the likelihood for a property damage only accident increases. Older drivers may be more tentative in their driving approach or more experienced in driving in adverse conditions and reacting appropriately.

Estimation results for ice-accident severity along principal arterials are presented in Table 5. Again, the presence of ice-warning signs did not have a statistically significant effect on accident severity. Other findings show that ice-related accidents involving residents living within 24 km of the accident site were less likely to result in a fatality but more likely to result in an injury on principal arterial state highways. Ice accidents involving residents living more than 24 km from the site of the accident were also more likely to result in an injury. Along State Route 503, injuries were less likely to result. Characteristics or features of this roadway that preclude injury occurrence are unclear and need to be studied further.

With variation in winter severity from year to year, one may expect some temporal variation in ice-related accident severity. Accidents occurring in 1994 were more likely to result in injury than accidents occurring in other data years (i.e. 1993, 1995). Table 5 also shows that a number of accident characteristics were found to have a significant effect on ice-accident severity. As the number of vehicles involved in the accident increased so did the likelihood for both injury and fatality. If fuel was spilled during the accident, typifying a more severe accident, the likelihood for a fatality increased. Injuries were more likely to result if a vehicle crosses the centerline and one would suspect an increased occurrence of fatalities as well under these circumstances although this variable was not found to be significant.

Finally, estimation results for minor arterial ice-accident severity are presented in Table 6. The presence of ice-warning signs once again did not have a statistically significant effect on accident severity. On minor arterial state highways, ice-related accidents occurring in WSDOTs Olympic Region were found to be more likely to result in a fatality while accidents occurring in the Southwest Region were less likely to result in injury. Seasonal and topographic variations among the locales, as well as driver experience under the various environmental conditions, likely explain the differences noted here. Accidents occurring on State Routes 6 and 7 were more likely to result in a fatality while accidents occurring on State Route 161 were more likely to result in injury. Again, unique roadway characteristics or features likely explain these differences.

Ice-related accidents were more likely to result in a fatality if occurring in February as opposed to other months of the year. Motorists may be anticipating an early spring and prematurely relaxing their caution to freezing temperatures — although numerous other explanations are possible. Ice accidents involving trucks under 45 000 N were more likely to result in injury. Ice accidents involving single unit trucks over 45 000 N were also more likely to result in injury but at a significantly higher probability as indicated by the relative magnitude of the coefficients of these two variables. One would suspect that the involvement of larger vehicles would also lead to an increased occurrence of fatalities however, this variable was not found to be significant.

6. Summary and conclusions

Our review of ice-warning sign placement nationally, and in Washington State, indicates that there is a lack of consistency and common policy guidelines bringing into question the effectiveness of ice-warning signs in reducing the frequency and severity of vehicular accidents (for a detailed review of ice-warning sign placement practices please see Carson, 1998). The effect of ice warning signs on ice accident frequencies and severities was investigated using appropriate statistical models. These statistical models were estimated using three years of ice-accident data from Washington State.

Our findings show that ice-warning signs do not have a statistically significant impact on the frequency or severity of vehicular accidents that involve ice. This suggests that current ice-warning sign placement practices are ineffective and that there is an urgent need for standardized sign-placement procedures that will reduce the frequency and severity of ice-related accidents.

Our statistical analysis also isolates a variety of factors that significantly influence the frequency and severity of ice-related accidents in Washington State. These factors show a complex relationship and one that is often location-specific (as suggested by the significance of regional and route indicator variables). The information provided by our study can be used as a starting point to improve ice-warning sign placement practices in Washington State. For other states, the methodological approach we adopt can be used to develop similar statistical models to provide sign-placement guidance. An important area of future research would be to collect ice-related accident data from a number of states and test the transferability of findings from one state to the next and to see if any state has current sign-placement strategies that do significantly reduce the frequency and severity of accidents.

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