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Impact of roadside features on the frequency and severity of run-off-roadway accidents: an empirical analysis

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Abstract

In the US, single-vehicle run-off-roadway accidents result in a million highway crashes with roadside features every year and account for approximately one third of all highway fatalities. Despite the number and severity of run-off-roadway accidents, quantification of the effect of possible countermeasures has been surprisingly limited due to the absence of data (particularly data on roadside features) needed to rigorously analyze factors affecting the frequency and severity of run-off-roadway accidents. This study provides some initial insight into this important problem by combining a number of databases, including a detailed database on roadside features, to analyze run-off-roadway accidents on a 96.6-km section of highway in Washington State. Using zero-inflated count models and nested logit models, statistical models of accident frequency and severity are estimated and the findings isolate a wide range of factors that significantly influence the frequency and severity of run-off-roadway accidents. The marginal effects of these factors are computed to provide an indication on the effectiveness of potential countermeasures. The findings show significant promise in applying new methodological approaches to run-off-roadway accident analysis. © 2002 Elsevier Science Ltd. All rights reserved.

Keywords: Run-off-roadway; Countermeasures

1. Introduction

Many state transportation agencies have accident prevention and mitigation programs that involve the analysis of roadside features. In Washington State, about one-fourth of traffic accidents are associated with vehicles running off the road and the characteristics of roadside features have a significant effect on both the frequency and severity of such accidents. In the U.S., single-vehicle run-off-roadway accidents result in over a million highway crashes with roadside features every year. Such accidents account for about one third of all highway fatalities, with an estimated societal cost of over $80 billion (NCHRP, 1997). These statistics on roadside-related vehicular accidents indicate the continued need for research to develop cost-effective countermeasures to reduce their frequency and severity.

A number of recent studies have specifically addressed run-off-roadway accidents and the effect that roadside features have on such accidents. Some of this work has dealt with the likelihood of accidents caused by roadside features at a general level (Mak, 1995) and the aggregate effect of roadside feature countermeasures on injury reduction (summarized in Elvik, 1999). Other run-off-roadway accident studies have examined particular roadside features such as roadway guardrail systems, utility poles, bridges, sign supports, side slopes and ditches and fences and their effect on the frequency and severity of accidents Turner, 1984; Good et al., 1987; Gattis et al., 1993; Viner, 1993; Michie and Bronstad, 1994; Viner, 1995; Zegeer and Council, 1995; Kennedy, 1997; Mauer et al., 1997; Reid et al., 1997; Ogden, 1997; Wolford and Sicking 1997; Bateman et al., 1998; Ray 1999). However, the chronic lack of detailed roadside data, due primarily to the cost of collecting and maintaining such data, has been an obstacle to the development of detailed statistical models of the relationship between roadside features and

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accident frequency and severity (Hadi et al., 1995; Council and Stewart, 1996; Miaou, 1997).

The intent of our research is to develop statistical models that provide additional insight into the impact that roadside features have on the frequency and severity of run-off-roadway accidents. We do this by using an extensive roadside-feature database recently collected from State Route 3 in Washington State and combining these data with the State's accident and roadway geometric data files. The combination of these data give a very rich source that allows isolation of the impact of roadside features on run-off-roadway accident frequency and severity while accounting for geometric features, traffic conditions, driver behavior, environmental conditions, and other factors that affect the frequency and severity of run-off-roadway accidents.

2. Methodological approach — accident frequency analysis

In terms of methodological perspectives, many applications of statistical modeling of accident frequency have been undertaken in recent years. However, some methodological approaches have been shown to be superior to others. For example, Jovanis and Chang (1986), Joshua and Garber (1990), and Miaou and Lum (1993) demonstrated that conventional linear regression models are inappropriate in modeling accident frequencies, and they found inferences drawn from these models are often erroneous. Categorical modeling techniques, such as logit models and other discrete-outcome models are also inappropriate for modeling accident frequencies because they do not account for the non-negative integer 'count' characteristic of frequency data. In accident analysis and other fields of study (e.g. economics and modeling of transportation behavior) the consensus of all contemporary empirical work is that poisson and negative binomial regression count models are the most appropriate methodological techniques for frequency modeling. Following this, there have been numerous applications of Poisson and negative binomial regression models to accident frequency analysis (Miaou and Lum, 1993; Shankar et al., 1995; Poch and Mannering, 1996; Milton and Mannering 1998).

As an extension of standard Poisson and negative binomial regression, zero-inflated probability processes, such as the zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) regression models have gained considerable recognition in accident frequency analysis (Miaou, 1994; Shankar et al., 1997). These models account for the fact that the traditional application of poisson and negative binomial models does not address the posibility of zero-inflated counting processes. Zero-inflation may be present because some roadway sections can have accident probabilities that are so low over some time period that they can be considered to be virtually safe (in a zero-accident state). Other roadway sections may follow a normal count process for accident frequency in which non-negative integers (i.e. including zero) are possible accident frequency outcomes over a specified time period.

To illustrate the family of count-model alternatives as applied to accident frequency (number of accidents on a roadway section in some time period) we start with the Poisson model. In applying Poisson regression in accident frequency analysis, let n_{ij} be the number of run-off-roadway accidents on roadway section i during period j. The Poisson model is,

$$P(n_{ij}) = \frac{\exp(-\lambda_{ij})\lambda_{ij}^{n_{ij}}}{n_{ij}!}, \tag{1}$$

where $P(n_{ij})$ is the probability of n accidents occurring on a highway section i in time period j and λ_{ij} is the expected value of n_{ij},

$$E(n_{ij}) = \lambda_{ij} = \exp(\beta X_{ij}), \tag{2}$$

for a roadway section i in time period j, β is a vector of unknown regression coefficients that can be estimated by standard maximum likelihood methods (Greene, 1987), X_{ij} is a vector of variables describing roadway section geometric characteristics, environmental characteristics and other relevant roadside feature conditions that affect accident frequency.

A well-known limitation of the Poisson distribution is that the variance and mean must be approximately equal. The possibility of overdispersion (having variance exceeding the mean, rather than equaling the mean as the Poisson requires) is always a concern in modeling accident frequency and may result in biased, inefficient coefficient estimates. To relax the overdispersion constraint imposed by the Poisson model, a negative binomial distribution (based on a Gamma-distributed error term) is commonly used (Miaou, 1994; Shankar et al., 1995, 1998; Milton and Mannering, 1998; Carson and Mannering, 2001). The negative binomial model is derived by rewriting Eq. (2) such that,

$$\lambda_{ij} = \exp(\beta X_{ij} + \varepsilon_{ij}), \tag{3}$$

where $\exp(\varepsilon_{ij})$ is a Gamma-distributed error term, and this addition allows the variance to differ from the mean as below,

$$\mathrm{Var}\,[n_{ij}] = E[n_{ij}]\,[1 + \alpha E\,[n_{ij}]] = E[n_{ij}] + \alpha E[n_{ij}]^2. \tag{4}$$

The Poisson regression model is regarded as a limiting model of the negative binomial regression model as α approaches zero, which means that the selection between these two models is dependent upon the value of α. The negative binomial distribution has the form,

$$P(n_{ij}) = \frac{\Gamma((1/\alpha)+n_{ij})}{\Gamma(1/\alpha)n_{ij}!}\left(\frac{1/\alpha}{(1/\alpha)+\lambda_{ij}}\right)^{1/\alpha}\left(\frac{\lambda_{ij}}{(1/\alpha)+\lambda_{ij}}\right)^{n_{ij}}. \quad (5)$$

Standard maximum likelihood methods can be used to conduct the estimation of λ_{ij} (Greene, 1987).

To address the possibility of zero-inflated accident counting processes on roadway sections, the zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) regression models have been developed. Both zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) assume that two different processes are at work for some zero-accident count data. One process is the zero-accident state where the roadway section is virtually safe. The other process has the roadway section in a non-negative count state for accident frequency (i.e. a state that has a frequency outcome determined by a Poisson or negative binomial distribution). The zero-inflated Poisson (ZIP) assumes that the events, $Y=(Y_1, Y_2, \ldots, Y_n)$, are independent and (suppressing the j subscripting to simplify the notation),

$$Y_i = 0 \quad \text{with probability } p_i + (1-p_i)\exp(-\lambda_i), \quad (6)$$

$$Y_i = y \quad \text{with probability } (1-p_i)\exp(-\lambda_i)\,\lambda_i^y/y!,\quad y = 1, 2, \ldots, \quad (7)$$

where y is the number of accidents. Maximum likelihood methods are used to estimate the coefficients of a zero-inflated Poisson (ZIP) regression model and confidence intervals can be constructed by likelihood ratio tests.

The zero-inflated negative binomial (ZINB) regression model follows a similar formulation with events, $Y=(Y_1, Y_2, \ldots, Y_n)$, being independent and,

$$Y_i = 0 \quad \text{with probability } p_i + (1-p_i)\left[\frac{1/\alpha}{(1/\alpha)+\lambda_i}\right]^{1/\alpha}, \quad (8)$$

$$Y_i = y \quad \text{with probability } (1-p_i)\left[\frac{\Gamma((1/\alpha)+y)u_i^{1/\alpha}(1-u_i)^y}{\Gamma(1/\alpha)y!}\right],\quad y = 1, 2, \ldots \quad (9)$$

where $u_i = (1/\alpha)/[(1/\alpha)+\lambda_i]$.

Maximum likelihood methods are again used to estimate the coefficients of a zero-inflated negative binomial (ZINB) regression model.

The choice of an appropriate accident frequency model, zero-inflated or not, is critical. However, one cannot test this directly because the traditional Poisson or negative binomial model and their zero-inflated counterparts are not nested. To test the appropriateness of using a zero-inflated model rather than traditional model, Vuong (1989) proposed a test statistic for non-nested models that is well suited for situations where the distribution is specified. The statistic is determined computing,

$$m_i = \ln\left(\frac{f_1(y_i|X_i)}{f_2(y_i|X_i)}\right), \quad (10)$$

where $f_1(y_i|X_i)$ is the probability density function of the zero-inflated model and $f_2(y_1|X_i)$ is the probability density function of the Poisson or negative binomial distribution. Using this, Vuong's statistic for testing the non-nested hypothesis of a zero-inflated model versus traditional model is (Greene, 1987; Shankar et al., 1997),

$$V = \frac{\sqrt{n}\left[(1/n)\sum_{i=1}^{n} m_i\right]}{\sqrt{(1/n)\sum_{i=1}^{n}(m_i-\bar{m})^2}} = \frac{\sqrt{n}(\bar{m})}{S_m}, \quad (11)$$

where $\bar{m}$ is the mean, S_m is standard deviation, and n is a sample size. Vuong's value is asymptotically standard normally distributed, and if $|V|$ is less than 1.96 (the 95% confidence level for the t-test), the test does not indicate another model form. However, the zero-inflated regression model is favored if the V value is greater than 1.96, while a V value of less than -1.96 favors the Poisson or negative binomial regression model (Greene, 1987).

3. Methodological approach — accident severity analysis

The severity of an accident is often measured as the level of injury sustained by the most severely injured vehicle occupant (Chang and Mannering, 1999). This typically includes severity levels of: no injury (property damage only), possible injury, evident injury, disabling injury and fatality. Thus the severity level is a discrete outcome. An appropriate method of modeling such data is the multinomial logit (MNL) formulation, which has been previously applied to accident severity analysis (Shankar and Mannering 1996; Chang and Mannering 1999; Shankar et al., 2000; Carson and Mannering, 2001). Such a model is used to estimate the probability that vehicular accident n is severity i by determining the likelihood of discrete outcomes (severity categories) occurring given that accident has happened. Formally, the following probability statement holds

$$P_n(i) = P(S_{in} \geq S_{1n}) \quad \forall I \neq i, \quad (12)$$

where $P_n(i)$ is the probability that a discrete outcome i (accident severity category i) occurs in run-off-roadway accident n, where P denotes probability and S_{in} is a function that determines the severity of accident n. This function can be linearly formed such that,

$$S_{in} = \beta_i X_n + \varepsilon_{in}, \quad (13)$$

where β_i is a vector of statistically estimable coefficients, and X_n is a vector of measurable characteristics that determine severity (e.g. roadside characteristics, socioeconomic factors, vehicular type, roadway geometric factors, and so on), and ε_{in} is a disturbance term influencing run-off-roadway accident severity and is independent in each of the severity categories. By assuming that the disturbances (ε_{in}'s) are generalized extreme value (GEV) distributed, a multinomial logit (MNL) model can be derived to estimate the probability of run-off-roadway accident severity (McFadden, 1981),

$$P_n(i) = \left[\sum_I \exp[\beta_I X_n]\right]^{-1} \exp[\beta_i X_n], \tag{14}$$

where all variables are as previously defined and the coefficient vector β_i is estimable by standard maximum likelihood techniques.

The basic assumption in the derivation of the simple multinomial logit model is that disturbances (ε_{in}'s) are independent from one accident severity category to another. If some severity categories share unobserved effects (i.e. have correlated disturbances), the model derivation assumptions are violated and serious specification errors will result. However, if shared unobservables are present in the model structure, the generalized extreme value (GEV) distribution can be applied to provide a more generalized form of the accident severity probabilities. This is referred to as a nested logit model, which groups alternatives with correlated error terms into a nest by estimating a model that includes only accidents with outcomes in the nested grouping. The model has the following form (McFadden, 1981),

$$P_n(i) = \exp[\beta_i X_n + \Theta_i L_{in}]/\sum_I \exp[\beta_i X_n + \Theta_i L_{in}], \tag{15}$$

$$P_n(k|i) = \exp[\beta_{k|i} X_n]/\sum_K \exp[\beta_{k|i} X_n], \tag{16}$$

$$L_{in} = \ln\left[\sum_K \exp(\beta_{k|i} X_n)\right], \tag{17}$$

where $P_n(i)$ is the unconditional probability of accident n having severity i, X_n is a vector of measurable characteristics that determine accident severity, $P_n(k|i)$ is the probability of accident n having severity k conditioned on the severity being in severity category i, K 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), and Θ_i is an estimable coefficient with a value between 0 and 1 to be consistent with the model derivation (McFadden, 1981).[1] The nested logit model structure will cancel out shared unobserved effects in each nest, thus preserving the assumption of independence of unobserved effects for model derivation.

[1] Note that if Θ_i is equal to 1, Eqs. (15)–(17) reduce to Eq. (14) and there is no significant problem with shared unobservables.

4. Empirical setting

The roadside feature data available for this study were collected on a 96.6-km section of State Route 3, which is located 37 km west of Seattle. These data were collected in the northbound direction of this route using global positioning system (GPS) over a period from May 1998 to September 1998. The precise location of roadside features was collected in the area between the outside shoulder edge of the roadway and the right-of-way limits. To investigate the relationship between run-off-roadway accidents and roadway geometrics, environmental factors, driver characteristics, and roadside features, the roadside-feature database was combined with two additional databases; the Washington State accident database and the Washington State roadway geometric/traffic database. For our run-off-roadway accident frequency and severity analysis, information from the accident database was extracted from January 1, 1994 to December 31, 1996 from State Route 3. These data were combined with the roadway geometric/traffic database, which includes geometric measurement information on lanes, shoulders, medians, intersections, vertical and horizontal alignments and traffic information such as traffic volume, truck volume as a percentage of daily traffic, peak hour volume and legal speed limit.

After integrating these three databases into one, the resulting data were segmented into a total of 120 sections of equal 805 m length over the 96.6 km of State Route 3. These roadway sections will form the basis of accident frequency modeling (accidents per section per month).[2] A total of 489 run-off-roadway accidents were reported in the northbound direction of State Route 3 in the years 1994, 1995, and 1996. Table 1 provides a

[2] In terms of fixed-length section, Shankar et al. (1995) addressed the issues relating to roadway section length determination. They found that the disadvantages of using fixed-length sections are far less severe than using homogeneous sections (an obvious alternative). The unequal length of homogeneous sections rather than the equal fixed-length sections may exacerbate potential heteroskedasticity problems and result in a loss in model estimation efficiency. As a result of their findings, equal fixed-length sections were used. Also, in determining the appropriate fixed section length, a trade-off must be made in making the section length long enough to have variations in roadside features and short enough to geographically identify problematic roadway areas. After extensive analysis of the data, the 805 m section length was selected to give 120 equal-length sections. Our analysis with significantly shorter section lengths (200 sections of 483 m) showed fewer variables being significant in the accident frequency models whereas longer sections (up to 1932 m) did not result in more significant variables.

summary of crashes with roadside objects during this period and Table 2 provides summary information on some of the key roadway section characteristics available in the database.

5. Model estimation — accident frequency

Run-off-roadway accident frequency model estimation results showed that there was a significant difference in the factors that determined run-off-roadway accident frequencies (accidents per month on roadway sections) in urban and rural areas.[3] The reason for this is that, in addition to the many physical differences between urban and rural sections that are accounted for in our data, there are likely to be unobserved human factor and driver-behavior differences that explain why urban and rural frequency data are so different. For example, there could be differences in the urban and rural driving populations as well as changes in individual driver behavior as the amount of visual 'noise' changes from rural to urban environs.

Table 1
Crashes with roadside objects on State Route 3 (percent in parenthesis)

Roadside object	Number of crashes	
Guardrail	57	(15.36)
Earth bank	55	(14.82)
Ditch	42	(11.32)
Tree	42	(11.32)
Concrete barrier	38	(10.24)
Over embankment	31	(8.36)
Utility pole	20	(5.39)
Wood sign support	19	(5.12)
Bridge rail	17	(4.58)
Culvert	7	(1.89)
Boulder	6	(1.62)
Light poles	6	(1.62)
Mailbox	5	(1.35)
Fence	5	(1.35)
Building	5	(1.35)
All others	16	(4.32)

For urban section run-off-roadway accident frequency, the negative binomial regression model was found to be the most appropriate count model. The overdispersion parameter α was statistically significant (t-statistic of 2.680) indicating the appropriateness of the negative binomial regression model relative to the poisson regression model. This was validated when the zero-inflated negative binomial model specification failed to provide a statistically better fit (the Vuong statistic was -0.00003, which is less than the 1.96 that corresponds to the 95% confidence limit of the t-test).

For rural section run-off-roadway accident frequency, the zero-inflated negative binomial regression model was determined to be the most appropriate model. Zero-inflation was confirmed (the Vuong statistic of 4.731 was greater than the 1.96 corresponding to the 95% confidence level) indicating the appropriateness of the zero-inflated negative binomial regression model over a simple negative binomial model and the overdispersion parameter α remained significant (t-statistic of 1.891). To save space, we only present detailed model results from the rural frequency model estimation (urban model results are available in Lee, 2000). The model results for the zero-inflated negative binomial specification for rural section run-off-roadway accident frequency are presented in Table 3. The coefficients for both non-zero-accident state and zero-accident state were found to be statistically significant and of plausible sign.

In viewing the results in Table 3, it is important to note that the legal speed limit variable could not be used directly because of its endogenous relationship with run-off-roadway accident frequency. That is, although the legal speed limit potentially affects run-off-roadway accident frequency, roadway sections with high accident frequencies may be given lower speed limits as a countermeasure. To account for this endogeneity, we used an instrumental variable for speed limit in model estimation. The best model fit was found when using a legal speed limit indicator (1 if the legal speed limit is greater than 85 km/h, 0 otherwise). This one–zero variable was instrumented by estimating a binary logit model that was estimated using only exogenous independent variables. The resulting logit model was used to calculate the probability that the roadway section has a speed limit greater than 85 km/h. These estimated probabilities were used in place of the legal speed limit variable when estimating the run-off-roadway accident frequency model.

Turning to the estimation findings, we find a higher number of accidents were likely to occur in 1995 (positive coefficient in the negative binomial accident state). This could be due to seasonal variations and unob-

[3] We define urban sections as those roadway sections within an incorporated urban area, partially (in the case where a constant-length section straddles an urban boundary) or completely, and rural sections are all others. To test for differences in urban and rural accident frequency models we apply the likelihood ratio test statistic which is $-2[L_r(\beta) - L_U(\beta) - L_R(\beta)]$ where $L_r(\beta)$ is the log-likelihood at convergence of the model estimated on the all sections, $L_U(\beta)$ is the log-likelihood at convergence of the model estimated on the Urban sections, and $L_R(\beta)$ is the log-likelihood at convergence of the model estimated on the Rural sections. This statistic is χ^2 distributed with the degrees of freedom equal to the summation of the number of coefficients estimated in the urban and rural section models minus the total number of estimated coefficients in the 'all' section model. The results of the test indicate that there we are over 99% confident that there is a difference between urban and rural run-off-roadway accident frequency models frequency models ($\chi^2 = -2[-1522.09 - (-665.96) - (-797.40)] = 117.38$, degrees of freedom = 15).

Table 2
Summary statistics for roadway sections

Variable	Mean	Minimum	Maximum	Standard deviation
Total section run-off-roadway accident frequency (per month)	0.11	0	9	0.37
Urban section run-off-roadway accident frequency (per month)	0.06	0	9	0.27
Rural section run-off-roadway accident frequency (per month)	0.06	0	6	0.25
PDO run-off-roadway accident frequency (per month)	0.07	0	8	0.28
Possible injury run-off-roadway accident frequency (per month)	0.02	0	5	0.14
Evident injury run-off-roadway accident frequency (per month)	0.02	0	2	0.15
Disabling injury or fatality run-off-roadway accident frequency (per month)	0.01	0	1	0.08
Lane width (m)	3.64	1.93	5.89	0.38
Shoulder width (m)	1.79	0.49	3.17	0.85
Center shoulder width (m)	1.21	0	3.05	0.56
Shoulder length-left and right side (m)	1590	970	1610	80
Median width (m)	3.77	0	20.73	6.09
Legal speed limit (km/h)	84.10	42.53	96.56	12.20
Number of vertical curves	2.61	0	9	2.16
Vertical curve length (m)	78.14	0	426.72	78.18
Vertical grade (%)	0.80	0	3.04	0.72
Average annual daily traffic (AADT) per lane	2194	988	6522	998
Number of at-grade intersections	1.19	0	7	1.47
Guardrail length (m)	48.28	0	634.06	112.65
Distance from outside shoulder edge to guardrail (m)	0.67	0	5.05	1.11
Guardrail height (m)	0.20	0	1.52	0.33
Number of catch basins	0.93	0	15	2.76
Number of culverts	0.28	0	6	0.99
Distance from outside shoulder edge to ditch (m)	0.69	0	9.45	1.75
Ditch depth (m)	0.09	0	0.81	0.22
Fence length (m)	10	0	360	50
Distance from outside shoulder edge to fence (m)	1.06	0	14.07	2.83
Bridge length (m)	10	0	420	50
Distance from outside shoulder edge to side slopes (m)	1.10	0	8.89	2.03
Number of miscellaneous fixed objects	0.7	0	9	1.68
Distance from outside shoulder edge to miscellaneous fixed object (m)	1.19	0	17.07	2.79
Number of utility poles	3.83	0	32	6.75
Distance from outside shoulder edge to utility pole (m)	1.92	0	11.79	2.91
Number of sign supports	1.9	0	24	4.22
Distance from outside shoulder edge to sign support (m)	0.97	0	12.44	2.05
Number of light poles	0.76	0	30	3.27
Distance from outside shoulder edge to light poles (m)	0.83	0	8.23	1.97
Number of tree groups	1.66	0	26	4.16
Distance from outside shoulder edge to tree group (m)	1.32	0	17.8	3.11
Number of isolated trees	0.55	0	9	1.57
Distance from outside shoulder edge to isolated tree (m)	1.54	0	18.39	3.83

served effects associated with the severe rain and windstorms that plagued Washington in the winter of 1995. With regard to the speed limit indicator variable, speed limits above 85 km/h were found to increase the frequency of accidents in the negative binomial accident state (a positive coefficient) and decrease the likelihood of the roadway section being in the zero-accident state (a negative coefficient).

Increasing median width was found to reduce the likelihood of run-off-roadway accident occurrence (negative coefficient in the negative binomial accident state) suggesting that wider medians allow uncontrolled vehicles more space to recover and avoid a collision. In the negative binomial accident state, distance from the outside shoulder edge to light poles was found to decrease run-off-roadway accident frequencies. In contrast, the number of isolated trees and the presence of cut-slopes in the roadway right-of-way both contributed to increasing run-off-roadway accident frequency.

With regard to the zero-accident state, increasing shoulder width increased the probability that the roadway section would be in the zero-accident state reflecting the additional recovery space provided by wider shoulders. Longer vertical curve length was found to decrease run-off-roadway accident frequency in the negative binomial accident state and also to decrease the probability of roadway sections being in the zero-accident state. This indicates that longer vertical curve lengths push the model into the negative binomial

Table 3
Zero-inflated negative binomial estimation results[a]

Variable	Estimated coefficients	t-statistic
Negative binomial accident state		
Constant	−2.217	−8.007
Temporal characteristics		
Year of occurrence indicator 2 (1 if 1995, 0 otherwise)	0.221	1.527
Roadway characteristics		
Instrumented legal speed limit indicator (1 if the legal speed limit is greater than 85 km/h, 0 otherwise)	0.414	1.427
Median width (m)	−0.033	−5.331
Vertical curve length (m)	−0.002	−3.033
Roadside characteristics		
Cut side slope indicator (1 if the presence of cut-typed side slopes, 0 otherwise)	1.128	2.400
Distance from outside shoulder edge to light poles (m)	−0.029	−1.916
Number of isolated trees in a section	0.086	1.533
Dispersion parameter α	1.037	1.891
Zero-accident state		
Constant	0.917	1.509
Roadway characteristics		
Instrumented legal speed limit indicator (1 if the legal speed limit is greater than 85 km/h, 0 otherwise)	−3.501	−2.328
Shoulder width (m)	0.472	1.406
Vertical curve length (m)	−0.025	−2.526
Roadside characteristics		
Distance from outside shoulder edge to guardrail (m)	−0.320	−1.964
Restricted log-likelihood	−904.72	
Log-likelihood at convergence	−896.66	
Number of observations	2736	
Vuong statistic	4.731	

[a] Rural section per month run-off-roadway accident frequency.

accident state but decrease the frequency in this state. The greater the distance from the outside shoulder to the guardrail, the less likely the roadway section was in the zero-accident state. This may be an artifact of the data for those few roadway sections with large outside shoulder edge to guardrail distances.

To provide some insight into the implications of our estimation results, elasticities were computed to determine the marginal effects of the independent variables in the urban and rural run-off-roadway accident frequency models. Elasticity of run-off-roadway frequency λ_{ij} is defined as,

$$E_{x_{ijk}}^{\lambda_{ij}} = \frac{\partial \lambda_{ij}}{\partial x_{ijk}} \times \frac{x_{ijk}}{\lambda_{ij}}, \tag{18}$$

where E represents the elasticity, x_{ijk} is the value of the kth independent variable for section i in month j, and λ_{ij} is the mean run-off-roadway accident frequency on roadway section i in month j. However, the elasticity in Eq. (18) is only appropriate for continuous variables such as shoulder width, distance from outside shoulder edge to roadside features and vertical curve length. It is not valid for our non-continuous variables, indicator variables (i.e. those dummy variables that take on values of zero or one). For indicator variables, a ‘pseudo-elasticity’ can be computed to estimate an approximate elasticity of the variables. The pseudo-elasticity gives the incremental change in run-off-roadway frequency caused by changes in the indicator variables. The pseudo-elasticity is defined as,

$$E_{x_{ijk}}^{\lambda_{ij}} = \frac{\exp(\beta) - 1}{\exp(\beta)}. \tag{19}$$

The elasticities for each of the independent variables are shown in Table 4. The interpretation of elasticities is straightforward and gives a good indication of the relative importance of variables (which would be critical for using our findings for safety improvement priority programming). As an example, a 1% increase in median width causes a 0.526% reduction in run-off-roadway accident frequencies. Similarly, if cut-typed side slopes are present in rural areas, the accident rate will be 67.6% higher than roadway sections without such slopes.

Table 4
Elasticity estimates for rural section run-off-roadway accident frequency

Variable	Elasticity
Negative binomial accident state	
High speed limit probability	0.254
Median width (m)	−0.526
Vertical curve length (m)	−0.379
Cut side slope indicator (1 if the presence of cut-typed side slopes, 0 otherwise)	0.676
Distance from outside shoulder edge to light poles (m)	−0.055
Number of isolated trees in a section	0.026
Zero-accident state	
High speed probability	−1.215
Shoulder width (m)	1.214
Vertical curve length (m)	−1.468
Distance from outside shoulder edge to guardrail (m)	−0.814

6. Model estimation — accident severity

Using the same data as that used for accident frequency modeling, a nested logit model of the severity of the 489 run-off-roadway accidents reported in the northbound direction of SR-3 in Washington State from 1994 to 1996 is estimated. As previously mentioned, severity is defined as the level of injury sustained by the most severely injured vehicle occupant which includes severity levels of; no injury (property damage only), possible injury, evident injury, disabling injury and fatality. Because severity modeling is conditional (i.e. conditioned on an accident having occurred), data from detailed accident reports that include time of accident, effects of weather on pavement conditions (e.g. icy, wet, dry), driver-related data (age, gender, and so on), the number of vehicles involved in the accident, and vehicle-related data can now be used.

Of the 489 run-off-roadway accidents reported, 284 (58.1%) resulted in no injury (property damage only), 82 (16.8%) involved possible injury, 94 (19.2%) involved evident injury, and 25 (5.1%) resulted in disabling injury and 4 (0.8%) in fatalities.[4]

Turning to estimation findings, it was again determined that the effects of roadway geometric and roadside characteristics on run-off-roadway accident severity are appropriately modeled using a nested logit model and that urban and rural accidents should be modeled separately.[5] Although all possible nested structures were considered to capture the correlation among

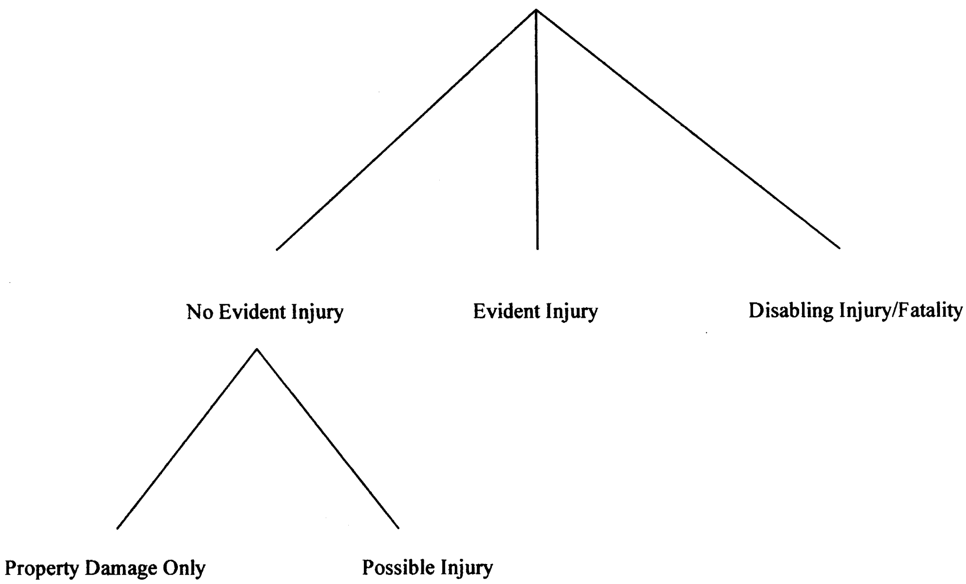

Fig. 1. Nested structure of run-off-roadway accident severities.

[4] Because of the low number of fatalities, we combine disabling injuries and fatalities in our analysis so only four alternatives are considered (property damage only, possible injury, evident injury, and disabling injury/fatality).

[5] As with accident frequency modeling, we test for differences in urban and rural accident severity models by applying the likelihood ratio test $(-2[L_r(\beta) - L_U(\beta) - L_r(\beta)]$ where $L_r(\beta)$ is the log-likelihood at convergence of the model estimated on accidents, $L_U(\beta)$ is the log-likelihood at convergence of the model estimated on the Urban accidents, and $L_R(\beta)$ is the log-likelihood at convergence of the model estimated on the Rural accidents). This statistic is χ^2 distributed with the degrees of freedom equal to the summation of the number of coefficients estimated in the urban and rural accident models minus the total number of estimated accients in the 'all' section model. The results of the test indicate that there we are over 95% confident that there is a difference between urban and rural run-off-roadway accident frequency models frequency models ($\chi^2 = -2[-308.60-(-147.36)-(-144.67)] = 32.10$, degrees of freedom $= 20$, $P = 0.033$).

Table 5
Estimation of property damage and possible injury probabilities of rural section run-off-roadway accident severity conditioned on no evident injury

Variable	Estimated coefficients	t-statistic
Constant (specific to property damage only)	3.050	3.792
Temporal characteristics		
Summer month indicator (1 if June, July, August or September, 0 otherwise; specific to possible injury)	1.115	2.365
Year of occurrence indicator (1 if 1995, 0 otherwise; specific to possible injury)	0.731	1.753
Environmental characteristics		
Clear/cloudy weather indicator (1 if run-off-roadway accidents occurred during clear or cloudy weather conditions, 0 otherwise; specific to possible injury)	1.026	1.590
Wet road surface indicator (1 if run-off-roadway accidents occurred on a wet road surface, 0 otherwise; specific to possible injury)	1.109	1.775
Driver characteristics		
Alcohol impaired driving indicator (1 if driver had not been drinking, 0 otherwise; specific to possible injury)	0.531	1.133
Inattention indicator (1 if 'inattention' is the primary contributing cause, 0 otherwise; specific to possible injury)	−0.690	−1.104
Young age driver indicator (1 if driver is at age of 25 or younger, 0 otherwise; specific to possible injury)	1.194	2.412
Roadway characteristics		
Curve indicator (1 if run-off-roadway accidents occurred on a horizontal curve, 0 otherwise; specific to possible injury)	0.863	2.030
Roadside characteristics		
Culvert indicator (1 if the presence of culverts, 0 otherwise; specific to possible injury)	1.550	1.262
Intersection indicator (1 if the presence of intersections, 0 otherwise; specific to possible injury)	−1.155	−1.630
Sign support indicator (1 if the presenceof sign supports, 0 otherwise; specific to possible injury)	−1.805	−1.651
Utility pole indicator (1 if the presence of utility poles, 0 otherwise; specific to possible injury)	1.918	1.803
Restricted log-likelihood	−121.99	
Log-likelihood at convergence	−78.97	
Number of observations	176	
ρ^2	0.35	

various severity levels, Fig. 1 gave the statistically correct nested structure.

As was the case for the accident frequency models, to save space, we present only those results for rural roadway sections. Estimation results for rural section run-off-roadway accident severity models are presented in Table 5 and Table 6.

Table 5 shows maximum likelihood estimation results for the lower level model (property damage only and possible injury) and Table 6 presents the estimation of overall rural section run-off-roadway accident severity model. The inclusive value coefficient shown in Table 6 is 0.261 and is significantly different from zero and one, suggesting that shared unobservables are present among lower levels (property damage only and possible injury). The lower and upper levels of the severity model resulted in good statistical fits as indicated by the log-likelihood at convergence and ρ^2 values, and all variable coefficients are of plausible sign and statistically significant.

Turning first to the results of the lower-nest model (the property damage only, and possible injury binary outcome model), it is found that accidents occurring in the summer months and in 1995 were more likely to result in possible injury (the higher severity of the two-outcome model). This summer finding may reflect drivers' higher travel speeds in the absence of inclement weather and the 1995 indicator variable accounts for the unique climatic factors during that year.

Accidents occurring during clear or cloudy conditions and on wet roads were more likely to result in possible injury (these findings are relative to ice and snow on the roadway and fog, raining and snowing conditions). This again may reflect, among other factors, higher driving speeds under these less severe roadway conditions. Drivers less that 25 years of age and alcohol impaired drivers were more likely to be involved in possible injury accidents while 'inattention' as the primary contributing cause was associated with the less severe property damage only outcome. The occurrence of an accident on a curve was more likely to result in a possible injury accident, as was an accident that occurred in areas with culverts and utility poles. In contrast, accidents occurring at intersections and with

Table 6
Estimation of overall nested logit model of rural section run-off-roadway accident severity probabilities

Variable	Estimated coefficients	t-statistic
Constant (specific to evident injury)	−1.985	−1.467
Constant (specific to disabling injury/fatality)	−2.352	−1.622
Temporal characteristics		
Day time indicator (1 if run-off-roadway accidents occurred at day time, 0 otherwise; specific to no evident injury)	−0.497	−1.282
Peak hour indicator (1 if run-off-roadway accidents occurred in the peak hours, 0 otherwise; specific to no evident injury)	−1.246	−3.001
Weekend indicator (1 if run-off-roadway accidents occurred during weekend, 0 otherwise; specific to disabling injury/fatality)	−1.223	−1.775
Year of occurrence indicator 1 (1 if 1994, 0 otherwise; specific to no evident injury)	−0.503	−1.296
Environmental characteristics		
Clear/cloudy weather indicator (1 if run-off-roadway accidents occurred during clear or cloudy weather conditions, 0 otherwise; specific to no evident injury)	−1.084	−1.856
Dry road surface indicator (1 if run-off-road-way accidents occurred on a dry road surface, 0 otherwise; specific to no evident injury)	−1.960	−3.484
Wet road surface indicator (1 if run-off-roadway accidents occurred on a wet road surface, 0 otherwise; specific to no evident injury)	−1.917	−2.869
Driver characteristics		
Alcohol impaired driving indicator (1 if driver had been drinking and ability impaired, 0 otherwise; specific to disabling injury/fatality)	1.189	2.013
Speeding indicator (1 if 'exceeded reasonably safe speed' was the primary contributing cause, 0 otherwise; specific to evident injury)	0.863	2.100
Roadway characteristics		
Asphalt shoulder indicator (1 if the surface of the shoulder is asphalt, 0 otherwise; specific no evident injury)	1.924	1.677
Instrumented legal speed limit indicator (1 if the legal speed limit is greater than 85 km/h, 0 otherwise; specific to disabling injury/fatality)	0.944	1.594
Narrow shoulder indicator (1 if shoulder width is less than or equal to 2 m, 0 otherwise; specific to disabling injury/fatality)	−1.030	−1.678
Roadside characteristics		
Instrumented guardrail indicator (1 if guardrail is present, 0 otherwise; specific to disabling injury/fatality)	0.723	2.073
Miscellaneous fixed object indicator (1 if the presence of miscellaneous fixed objects, 0 otherwise; specific to no evident injury)	0.990	1.198
Sign support indicator (1 if the presence of sign supports, 0 otherwise; specific to no evident injury)	0.890	1.338
Tree group indicator (1 if the presence of tree groups, 0 otherwise; specific to no evident injury)	−1.404	−2.740
Utility pole indicator (1 if the presence of utility poles, 0 otherwise; specific to no evident injury)	0.764	1.085
Inclusive value of property damage and possible injury (L_{in}, specific to no evident injury)	0.261	2.142
Restricted log-likelihood	−264.77	
Log-likelihood at convergence	−154.01	
Number of observations	241	
ρ^2	0.42	

sign supports were more likely to be property damage only.

With regard to the upper-nest model (see Fig. 1 and Table 6), accidents occurring in the day time, during peak hours, during clear or cloudy conditions (i.e. no precipitation or fog), on dry or wet roadway surfaces, and on roadway sections with tree groups on the side of the roadway were all less likely to be of the no evident injury category (i.e. property damage only or possible injury). Equivalently these factors increase the likelihood of evident injury and disabling injury/fatality. In contrast, accidents occurring in 1994, on roadway sections with miscellaneous fixed objects, with utility poles, with sign supports, with shoulder widths less than 2 m, and those with asphalt shoulders were more likely to result in no evident injury accidents. These findings likely reflect climatic variations and driver/vehicle behavior interactions.

Having 'exceeded reasonably safe speed' as the primary contributing cause of the accident made the accident more likely to be evident injury. The presence of guardrails in the roadway section increased the chance of the accident being a disabling injury/fatality.[6] This does not necessarily bring into question the effectiveness of guardrails, but may simply be reflecting the physical complexity of the geography along certain roadway sections. Likewise, accidents that occurred on roadway sections with speed limits in excess of 85 km/h were also more likely to result in disabling injury/fatality — reflecting the effect of speed on severity. Finally, accidents that occurred on weekends were less likely to result in disabling injury/fatality. This may be the result of variations in driver behavior and/or the driver population on weekends.

As with the accident frequency models, elasticities were estimated to examine the marginal effects of the variables in the lower and upper nests of three models. For the discrete outcome case, elasticity is defined as

$$E_{x_n}^{P_n(i)} = \frac{\partial P_n(i)}{\partial x_n} \times \frac{x_n}{P_n(i)}, \tag{20}$$

where E is the direct elasticity, x_n is the value of the variables being considered to have effects on the run-off-roadway accident severity i, and $P_n(i)$ is the probability of run-off-roadway accident n being of severity i. Given Eqs. (14) and (20), the following can be written,

$$E_{x_n}^{P_n(i)} = \left[1 - \sum_{I_n} P_n(i)\right]\beta_i x_n, \tag{21}$$

where I_n is the set of severity level that have variable x_n in the severity function (i.e. S_{in} in Eq. (13)) and β_i is the estimated coefficient corresponding to the variable. However, the elasticity in Eq. (21) is only appropriate for continuous variables. For indicator variables, a 'pseudo-elasticity' can be used to estimate an approximate elasticity of the variables. The pseudo-elasticity is defined as,

$$E_{x_n}^{P_n(i)} = \frac{\exp[\Delta(\beta_i X_n)] \sum_I \exp(\beta_i x_n)}{\exp[\Delta(\beta_i X_n)] \sum_{I=I_n} \exp(\beta_i X_n) + \sum_{I \neq I_n} \exp(\beta_i X_n)} - 1. \tag{22}$$

The elasticities are presented in Table 7 and interpretation is again straightforward. For example, the elasticity of alcohol impaired driving indicator is 0.143 for disabling injury/fatality. This means that accidents involving alcohol impaired driving are 14.3% more likely to be a disabling injury/fatality accident. Other examples show that the presence of guardrails (elasticity = 0.900) increases the probability of a disabling injury/fatality by 90%. And, the presence of tree groups along the roadway section decreases the likelihood of the accident not having an evident injury by 43.7%.

[6] As with the legal speed limit variable in the frequency analysis, the presence of guardrails could be influenced by the severity of accidents (i.e. roadway sections with a history of severe accidents may be more likely to have guardrails installed). To account for this endogeneity, an instrumental variable was again used in model estimation. This one–zero variable was instrumented by estimating a binary logit model that was estimated using only exogenous independent variables. The resulting logit model was used to calculate the probability of a guardrail being present. These estimated probabilities were used in place of the guardrail indicator variable when estimating the model.

7. Conclusions and recommendations

This study provides an empirical and methodological analysis of run-off-roadway accident frequency and severity. By accounting for relationships among roadway geometrics, roadside characteristics and run-off-

Table 7
Elasticity estimates for rural area run-off-roadway accident severity

Variable	Elasticity
Elasticity estimates for variables conditioned on no evident injury	
Wet road surface indicator (specific to possible injury)	1.210
Alcohol impaired driving indicator (specific to possible injury)	0.123
Inattention indicator (specific to possible injury)	−0.133
Young age indicator (specific to possible injury)	0.208
Curve indicator (specific to possible injury)	0.207
Culvert indicator (specific to possible injury)	0.386
Intersection indicator (specific to possible injury)	−0.203
Sign support indicator (specific to possible injury)	−0.790
Utility pole indicator (specific to possible injury)	2.537
Elasticity estimates for variables of overall nested logit model	
Day time indicator (specific to no evident injury)	−0.161
Peak hour indicator (specific to no evident injury)	−0.321
Weekend indicator (specific to disabling injury/fatality)	−0.684
Dry road surface indicator (specific to no evident injury)	−0.581
Wet road surface indicator (specific to no evident injury)	−1.920
Alcohol impaired driving indicator (specific to disabling injury/fatality)	0.143
Speeding indicator (specific to evident injury)	0.851
Asphalt shoulder indicator (specific to no evident injury)	0.778
High posted speed indicator (specific to disabling injury/fatality)	1.294
Narrow shoulder indicator (specific to disabling injury/fatality)	−0.007
Guardrail indicator (specific to disabling injury/fatality)	0.900
Miscellaneous fixed object indicator (specific to no evident injury)	0.300
Sign support indicator (specific to no evident injury)	0.478
Tree group indicator (specific to no evident injury)	−0.437
Utility pole indicator (specific to no evident injury)	0.424

roadway accident frequency and severity, this research provides some initial direction needed to identify cost-effective countermeasures that improve highway designs by reducing the probability of vehicles leaving the roadway and the severity of accidents when they do.

In terms of roadside treatments, our results show that run-off-roadway accident frequencies can be reduced by avoiding cut side slopes, decreasing the distance from outside shoulder edge to guardrail, decreasing the number of isolated trees along roadway sections, and increasing the distance from outside shoulder edge to light poles. Our results also show that run-off-roadway accident severity is a complex interaction of roadside features such as the presence of guardrails, miscellaneous fixed objects, sign supports, tree groups, and utility poles along the roadway. Some of these roadside features contribute to severity as the result of vehicle-object impact whereas others appear to mitigate severity, presumably by altering driver behavior (e.g. speed, awareness) in the roadway section.

The findings of this study are suggestive but limited in that they are based only on run-off-roadway accidents in the northbound direction of State Route 3 in Washington State. Due to limited data, we are unable to study run-off-roadway accident frequencies and severities on other functional classes (interstate, principal arterial, minor arterial and collector) nor could we study regional differences. The required cost for roadside field data collection makes it difficult to statistically model the relationship between roadside-struck objects and run-off-roadway accidents and there is still much work to be done as more and more data become available. Still, this study provides the Wahington State Department of Transportation a basis for developing effective countermeasures for run-off-roadway accidents in the State Route 3 corridor.

References

Bateman, M., Howard, I., Johnson, A., Walton, J., 1998. Model of the performance of a roadway safety fence and its use for design. Transportation Research Record 1647, 122–129.

Carson, J., Mannering, F., 2001. The effect of ice warning signs on accident frequencies and severities. Accident Analysis and Prevention 33 (1), 99–109.

Chang, L.-Y., Mannering, F., 1999. Analysis of injury severity and vehicle occupancy in truck- and non-truck-involved accidents. Accident Analysis and Prevention 31 (5), 579–592.

Council, F., Stewart, J., 1996. Severity indexes for roadside objects. Transportation Research Record 1528, 87–96.

Elvik, R., 1999. Can injury prevention efforts go too far? Reflections on some possible implications of vision zero for road accident fatalities. Accident Analysis and Prevention 31 (2), 265–286.

Gattis, J., Varghese, J., Toothaker, L., 1993. Analysis of guardrail — end accidents in Oklahoma. Transportation Research Record 1419, 52–62.

Good, M., Fox, J., Joubert, P., 1987. An in-depth study of accidents involving collisions with utility poles. Accident Analysis and Prevention 19 (5), 397–413.

Greene, W., 1987. Econometric Analysis, 3rd. Prentice Hall.

Hadi, M., Aruldhas, J., Chow, L.-F., Wattleworth, J., 1995. Estimating safety effects of cross-section design for various highway types using negative binomial regression. Transportation Research Record 1500, 169–177.

Joshua, S., Garber, N., 1990. Estimating truck accident rate and involvements using linear and poisson regression models. Transportation planning and Technology 15, 41–58.

Jovanis, P., Chang, H.-L., 1986. Modeling the relationship of accidents to miles traveled. Transportation Research Record 1068, 42–51.

Kennedy, J., 1997. Effect of light poles on vehicle impacts with roadside barriers. Transportation Research Record 1599, 32–39.

Lee, J. Econometric analysis of the effect of roadway geometric and roadside features on run-off-roadway accident frequencies and severities, doctoral dissertation, Department of Civil and Environmental Engineering, University of Washington, Seattle, WA.

Mak, K., 1995. Safety effects of roadway design decisions-roadside. Transportation Research Record 1512, 16–21.

Mauer, F., Bullard, L., Alberson, D., Menges, W., 1997. Development and testing of steel U-channel slip safe sign support. Transportation Research Record 1599, 57–63.

McFadden, D., 1981. Econometric models of probabilistic choice. In: Manski, C., McFadden, D. (Eds.), Structural Analysis of Discrete Data with Econometric Applications. MIT press, Cambridge, MA.

Miaou, S.-P., 1994. The relationship between truck accidents and geometric design of road sections: Poisson versus negative binomial regressions. Accident Analysis and Prevention 26 (4), 471–482.

Miaou, S.-P., 1997. Estimating vehicle roadside encroachment frequencies by using accident prediction models. Transportation Research Record 1599, 64–71.

Miaou, S.-P., Lum, H., 1993. Modeling vehicle accidents and highway geometric design relationships. Accident Analysis and Prevention 25 (6), 689–709.

Michie, J., Bronstad, M., 1994. Highway guardrails: safety feature or roadside hazard? Transportation Research Record 1468, 1–9.

Milton, J., Mannering, F., 1998. The relationship among highway geometrics, traffic-related elements and motor-vehicle accident frequencies. Transportation 25, 395–413.

NCHRP Research Results Digest 220,Strategies for improving roadside safety, Transportation Research Board, National Research Council, Washington, DC, November 1997.

Ogden, K., 1997. The effects of paved shoulders on accidents on rural highways. Accident Analysis and Prevention 29 (3), 353–362.

Poch, M., Mannering, F., 1996. Negative binomial analysis of intersection-accident frequencies. Journal of Transportation Engineering 122 (3), 105–113.

Ray, M., 1999. Impact conditions in side-impact collisions with fixed roadside objects. Accident Analysis and Prevention 31 (1), 21–30.

Reid, J., Sicking, D., Faller, R., Pfeifer, B., 1997. Development of a new guardrail system. Transportation Research Record 1599, 72–80.

Shankar, V., Mannering, F., Barfield, W., 1995. Effect of roadway geometrics and environmental factors on rural freeway accident frequencies. Accident Analysis and Prevention 27 (3), 371–389.

Shankar, V., Mannering, F., 1996. An exploratory multinomial logit analysis of single-vehicle motorcycle accident severity. Journal of Safety Research 27 (3), 183–194.

Shankar, V., Milton, J., Mannering, F., 1997. Modeling accident frequencies as zero-altered probability processes: an empirical inquiry. Accident Analysis and Prevention 29 (6), 829–837.

Shankar, V., Albin, R., Milton, J., Mannering, F., 1998. Evaluating median cross-over likelihoods with clustered accident counts: an empirical inquiry using the random effects negative binomial model. Transportation Research Record 1635, 44–48.

Shankar, V., Albin, D., Milton, J., Nebergall, M., 2000. In-service performance-based roadside design policy: preliminary insights from Washington State's bridge rail study. Forthcoming in Transportation Research Record.

Turner, D., 1984. Prediction of bridge accident rates. Journal of Transportation Engineering 110 (1), 45–54.

Viner, J., 1993. Harmful events in crashes. Accident Analysis and Prevention 25 (2), 139–145.

Viner, J., 1995. Rollovers on sideslopes and ditches. Accident Analysis and Prevention 27 (4), 483–491.

Vuong, Q., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. Econometrica 57, 307–334.

Wolford, D., Sicking, D., 1997. Guardrail need: embankment and culverts. Transportation Research Record 1599, 48–56.

Zegeer, C., Council, F., 1995. Safety relationships associated with cross-sectional roadway elements. Transportation Research Record 1512, 29–36.