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Safety impacts of signal-warning flashers and speed control at high-speed signalized intersections

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ABSTRACT

For many years, to reduce the crash frequency and severity at high-speed signalized intersections, warning flashers have been used to alert drivers of potential traffic-signal changes. Recently, more aggressive countermeasures at such intersections include a speed-limit reduction in addition to warning flashers. While such speed-control strategies have the potential to further improve the crash-mitigation effectiveness of warning flashers, a rigorous statistical analysis of crash data from such intersections has not been undertaken to date. This paper uses 10-year crash data from 28 intersections in Nebraska (all with intersection approaches having signal-warning flashers; some with no speed-limit reduction, and the others with either 5 mi/h or 10 mi/h reduction in speed limit) to estimate a random parameters negative binomial model of crash frequency and a nested logit model of crash-injury severity. The estimation findings show that, while a wide variety of factors significantly influence the frequency and severity of crashes, the effect of the 5 mi/h speed-limit reduction is ambiguous – decreasing the frequency of crashes on some intersection approaches and increasing it on others, and decreasing some crash-injury severities and increasing others. In contrast, the 10 mi/h reduction in speed limit unambiguously decreased both the frequency and injury-severity of crashes. It is speculated that the smaller distance covered during reaction time at lower speeds (allowing a higher likelihood of crash avoidance) and reduced energy of crashes associated with lower speed limits are not necessarily sufficient to overcome the increased speed variance caused by a speed-limit reduction in the 5 mi/h speed-limit reduction case – but they are sufficient to overcome the increased speed variance caused by a speed-limit reduction in the 10 mi/h case. Based on this research, speed-limit reductions in conjunction with signal-warning flashers appear to be an effective safety countermeasure, but only clearly so if the speed-limit reduction is at least 10 mi/h.

Key words:

Speed limit reduction, crash frequency, crash severity, nested logit model, random parameter negative binomial model, high-speed signalized intersection, signal-warning flashers

INTRODUCTION

Traffic-safety data indicate that greater than 20 percent of all traffic fatalities in the United States in occur at intersections. In 2010 alone, more than 6,700 fatalities occurred at intersections (National Highway Traffic Safety Administration, 2012). While many factors determine the likelihood of crashes in general, and fatal crashes in particular, at signalized intersections, signalized intersections with high approach speeds are particularly notorious for generating fatal crashes. At such high-speed intersections, studies have shown that the frequency and injury-severity of crashes can be reduced by countermeasures that involve speed-limit reductions on intersection approaches and/or the implementation of warning flashers to provide drivers with additional time to make safer intersection-related decisions (Antonucci et al., 2004).

With regard to speed-limit limit reductions in general, many studies have been conducted to test the effectiveness of changes in the speed limits due to regulations/laws, variable speed limits, dynamic message signs, and special transition zones (Buddemeyer et al., 2010; Cruzado and Donnell, 2010; Monsere et al., 2005; Parker, 1997; Son et al. 2009; Towliat et al., 2006; van den Hoogen and Smulders, 1994). Findings from these studies suggest that arbitrary changes in speed limit (changes without a reason that is immediately obvious to drivers) have little impact upon driver behavior, and may result in increased violation and low compliance. However, a speed reduction for certain special cases, such as a dangerous curves, or adverse weather conditions, has often been shown to lead to a significant reduction in operational speeds, even though the magnitude is typically less than the reduction of the posted speed limit. In addition, lowering the speed limit does not always improve safety because a possible increase in the variance of speeds may increase the frequency and severity of crashes because some drivers may continue to travel at a speed that they perceive to be reasonable and safe while other drivers may attempt to comply with the posted speed limit. The resulting increase in speed variance can completely offset the benefits of the reduced speed limit or in some cases actually result in more dangerous traffic conditions.[1]

In contrast to the speed limit reductions, signal-warning flashers are designed to alert drivers of forthcoming yellow signal indication at the intersection, giving them more time to adjust their speed accordingly. There have been a number of research efforts that have studied the effectiveness of these signal-warning flashers. For example, a study by Appiah et al. (2011) concluded that such signal-warning flashers resulted in a 8 percent reduction in the number of crashes. In other work, Burnett and Sharma (2011) found that the location and timing of signal-warning flashers were key determinants in the risk of severe deceleration and/or red-light running at high-speed intersections – both of which are fundamental factors in determining the frequency and severity of crashes. However, to date, the authors are not aware of any studies that have considered the joint effects of speed-limit reductions and signal-warning flashers at high-speed signalized intersections.

In terms of the implementation speed-limit reductions and signal-warning flashers at high-

[1] There are numerous studies that show this behavior. For example, Boyle and Mannering (2004) found in a simulator study that drivers given in-vehicle speed recommendations for adverse weather slowed down substantially relative to those drivers who were not given such in-vehicle information. However, these in-vehicle-information drivers sped up when the adverse conditions passed, to make up for lost time, causing a high variances in speed during and after the hazard. Also, Malyshkina and Mannering (2008) found that increasing speed limits on interstate highways by 5 mi/h in Indiana did not result in an increase crash-injury severities, partly because of the decline in speed variance at the higher speed limit.

speed intersections, a survey of eight U.S. states (Nebraska, Kansas, Iowa, Missouri, South Dakota, Wyoming, Colorado and California) indicated that they all used signal-warning flashers at high-speed intersections, and that the application of this technology is well supported by guidelines provided in the Manual of Uniform Control Devices (Federal Highway Administration, 2009). In contrast, guidelines for implementing speed-limit reductions at high-speed intersections do not exist, and most states generally do not apply reductions unless there are significant intersection-related safety concerns, such as a high crash history or a limited field of vision. The presence of signal-warning flashers further complicates the issue surrounding the necessity and effectiveness of speed-limit reductions. The combined presence of signal-warning flashers and speed-limit reductions can produce a range of possible outcomes. The expected outcome would be that reduced speed limits would be effective in reducing operating speeds in the presence of signal-warning flashers and thus enhancing overall safety. However, there is the possibility of more complicated effects such as heterogeneous compliance with the reduced speed limit. Such heterogeneity may be more likely to occur in the presence of signal-warning flashers (as drivers may differ greatly in their assessment of the safety benefits provided by both mitigation measures) and the resulting increase in the variance of vehicle speeds may compromise the net effect of both of these countermeasures.[2] This paper will investigate the safety effects of speed-limit reductions at high-speed intersections with signal-warning flashers, by considering their effects on crash frequencies and severities.

[2] There is some empirical evidence that shows that this increasing variance may not be a problem. For example, Wu et al. (2012) showed that the impact of a 10 mi/h speed-limit reduction (from 65 mi/h to 55 mi/h) at high-speed intersections with signal-warning flashers in Nebraska reduced mean operating speeds by 3.8 mi/h without significantly changing the standard deviation of speeds.

Empirical Setting

The crash dataset consists of crash data for 28 intersections in Nebraska, collected over a ten-year period from January 1, 2001 to December 31, 2010. As done in previous research (for example, Poch and Mannering, 1996), each intersection is broken up into approaches (lane groups at intersections such as northbound lanes, southbound lanes, eastbound lanes and westbound lanes) meaning that the typical intersection would generate 4 observations. However, consideration is only given to intersection approaches with signal-warning flashers – which gives a total of 56 approaches in the dataset. The crash data were grouped for each approach of the primary highway (the higher-volume highway) at each intersection and 43 of the 56 approaches had no reduction in speed limit (i.e., with 0 mi/h speed limit drop); nine approaches had a 5 mi/h speed limit drop; and four approaches had a 10 mi/h speed limit drop.[3]

The number of crashes occurring in each year is considered for each observation so the 56 approaches produce 560 observations because each approach has 10 years of crash data. However, two intersections had a history of stop-controlled approaches, as opposed to signalized approaches, within the 10-year study period, thus with these stop-controlled observations removed there were 536 observations for the approach-based annual crash-frequency model.

With regard to the severity of crashes, the data includes detailed police-reported crash data from 635 crashes that occurred during the study period. Each crash was documented together with

[3] The uneven number of approaches for 0 mi/h reduction and 5 mi/h reduction resulted from one intersection having asymmetrical signal approach speed; its northbound approach had a 0 mi/h reduction while its southbound approach had a 5 mi/h reduction.

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its crash characteristics, driver characteristics, and location-specific traffic characteristics including traffic control and traffic flow characteristics.

The main variables of interest were traffic-control characteristics including yellow time, flasher time, and speed-limit reductions, which were studied by defining indicator variables in statistical models. The descriptive statistics of some of the available variables are provided in Table 1.

METHODOLOGY – CRASH FREQUENCY

Count-data modeling techniques are commonly used for crash-frequency analysis because the number of crashes assigned to an intersection approach is a non-negative integer. These, count data are generally modeled with a Poisson regression or its derivatives which include the negative binomial and zero-inflated models (see Shankar et al., 1997; Lord and Mannering, 2010; Washington et al., 2011). For the basic Poisson model, the probability $P(n_i)$ of intersection approach i having n_i crashes per year is,

$$P(n_i) = EXP(-\lambda_i)\lambda_i^{n_i} / n_i! \tag{1}$$

where λ_i is the Poisson parameter for intersection approach i, which is intersection approach i's expected number of crashes, $E[n_i]$. Poisson regression specifies the Poisson parameter λ_i (the expected number of accidents) as a function of explanatory variables by using a log-linear function,

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

where $\mathbf{X}_i$ is a vector of explanatory variables and $\boldsymbol{\beta}$ is a vector of estimable parameters (Washington et al., 2011).

As is well known in the literature (Lord and Mannering, 2010), a Poisson model may not always be appropriate because the Poisson distribution restricts the mean and variance to be equal ($E[n_i] = VAR[n_i]$). Crash-frequency data are typically overdispersed ($E[n_i] < VAR[n_i]$) so estimation with a Poisson model will result biased parameter estimates. To account for this possibility, the negative binomial model is often used. This model is derived by rewriting,

$$\lambda_i = EXP(\boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i), \tag{3}$$

where $EXP(\varepsilon_i)$ is a Gamma-distributed error term with mean 1 and variance α^2. The addition of this term allows the variance to differ from the mean with $VAR[n_i] = E[n_i][1+ \alpha E[n_i]] = E[n_i]+ \alpha E[n_i]^2$. The negative binomial probability density function is (Washington et al., 2011):

$$P(n_i) = \left(\frac{1/\alpha}{(1/\alpha)+\lambda_i}\right)^{1/\alpha} \frac{\Gamma\left[(1/\alpha)+n_i\right]}{\Gamma(1/\alpha)n_i!} \left(\frac{\lambda_i}{(1/\alpha)+\lambda_i}\right)^{n_i} \tag{4}$$

where Γ(.) is a gamma function. Not that the Poisson regression is a limiting model of the negative binomial regression as α approaches zero. Thus, if α (often referred to as the dispersion parameter) is significantly different from zero, the negative binomial is appropriate and if it is not, the Poisson model is appropriate (Washington et al., 2011).

Random parameters can be introduced to account for possible heterogeneity (unobserved factors that may vary across intersections). In this case the model is structured so that each of the 28 intersections (each of which have two approaches) can have their own β. This is in contrast to the traditional random parameters approach where each observation (in this case each year/intersection-approach combination), would get their get their own β.[4] To develop such a random parameters model, individual estimable parameters are written as (see Greene, 2007; Anastasopoulos and Mannering, 2009; Washington et al., 2011),

$$\beta_j = \beta \;\; + \varphi_j \tag{5}$$

where φ_j is a randomly distributed term for each intersection *j*, and it can take on a wide variety of distributions such as the normal, log-normal, logistic, Weibull, Erlang, and so on. Given equation

[4] Note that, with ten years of data and typically two of the four intersection approaches having the signal-warning flashers, each intersection generates 20 observations.

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5, the Poisson parameter λ_i becomes $\lambda_i|\boldsymbol{\varphi}_j = EXP(\boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i)$ in the negative binomial model with the corresponding probabilities $P(n_i|\boldsymbol{\varphi}_j)$ (see Equation 1). The log-likelihood function for the random parameters negative binomial in this case can be written as,

$$LL = \sum_{\forall i} ln \int_{\varphi_j} g\left(\varphi_j\right) P\left(n_i \mid \varphi_j\right) d\varphi_j \tag{6}$$

where $g(.)$ is the probability density function of the φ_j.

Because maximum likelihood estimation of the random-parameters Poisson and negative binomial models is computationally cumbersome (due to the required numerical integration of the negative binomial function over the distribution of the random parameters), a simulation-based maximum likelihood method is used (the estimated parameters are those that maximize the simulated log-likelihood function while allowing for the possibility that the variance of φ_j for intersection-level parameters is significantly greater than zero). The most popular simulation approach uses Halton draws, which has been shown to provide a more efficient distribution of draws for numerical integration than purely random draws (see Greene, 2007).

Finally, to assess the impact of specific variables on the mean number of crashes, marginal effects are computed (see Washington et al., 2011). Marginal effects are computed for each observation and then averaged across all observations. The marginal effects give the effect that a one-unit change in x has on the expected number of crashes at each approach, λ_i.

ESTIMATION RESULTS: CRASH FREQUENCY

The parameter estimation results are shown in Table 2 and the corresponding average marginal effects are shown in Table 3. The model results in Table 2 show that the model includes 5 significant fixed parameters and 4 significant random parameters. Overall model fit is quite good as indicated by the log-likelihood at convergence (-732.05) which shows a very substantial improvement relative the log-likelihood with only the constant included in the model (-1104.00). Finally, with regard to overall model fit, the statistical significance of the dispersion parameter, α, shows that it significantly different from zero and that the negative binomial model is appropriate relative to the simple Poisson model.

Turning to specific parameter estimates, higher truck percentages produce a positive parameter indicating that an increase in truck percentages increases the frequency of crashes. This is expected given the poorer braking performance of trucks can be expected to be problematic at high-speed intersections. The marginal effects in Table 3 show that a 1% increase in truck percentage increases the mean number of crashes per year on the approach by 0.0142.

Also, as expected, increases in traffic volume per lane increase the frequency of crashes on intersection approaches. Here, marginal effects show that an increase in average traffic volume of 1,000 vehicles per day will increase the expected number of crashes by 0.24 per year (see Table 3). As this number indicates, any substantial increase in volume can be a real safety concern.

Intersection approaches with divided medians were found to have higher crash rates with marginal effects showing that a divided-median intersection approach has a 0.81 higher median crash rate relative to undivided median approaches. Here, the space between opposing lanes is likely causing the problem by increasing the time required to clear the intersections for vehicles crossing the approach lanes. Sight distance may also be an issue with divided medians in some cases.

The estimated parameter for the insufficient flasher-time indicator (see Table 1 for definition) was found to be a normally distributed random parameter with a slightly positive but insignificant effect on average (the parameter mean). However, this parameter estimate did have a highly statistically significant standard deviation. Given the estimated standard deviation, the variable mean, and the normal distribution of parameters, we find that the presence of insufficient flasher-time increases crash frequencies at 57% of intersections and decreases crash frequencies at 43% of intersections. The variation in this parameter about zero suggests that the influence of insufficient flasher times varies considerably among intersection approaches and this may be due to, among other things, how local drivers react to flashers. Because a large percentage of drivers on the intersection approaches are likely regular users, this finding may be picking up site-specific anomalies among intersections or the possibility that the driver populations adjust to minor variations in flashing times in different ways and this would explain the plus/minus variation in this parameter estimate.

The sufficient yellow-time indicator (see Table 1 for definition) also resulted in a normally distributed random parameter with a statistically insignificant mean and a significant standard deviation. In this case, intersections with sufficient yellow times had reduced crash frequencies 58% of the time and increased crash frequencies 42% of the time. Once again this heterogeneous effect across intersections may be the result of site-specific anomalies and/or adaptive driver behavior.

The percentage of total approach traffic making left turns also produced a normally distributed random parameter negative mean (although statistically insignificant from zero). The distribution of parameters is such that higher left-turn percentages have a negative effect on crash frequencies at 59% of the intersections and a positive effect on crash frequencies at 41% of the intersections. It is again speculated that this variation is likely the result of site-specific anomalies and diver adaptation.

Turning now to the specific variables of interest, the effect of various reductions in speed limit in the presence of warning flashers, we find that a 5 mi/h reduction results in a normally-distributed random parameter with a statistically significant mean of -0.32 and a standard deviation of 0.72. This suggests that the 5 mi/h speed-limit reduction reduces crash frequencies at 67% of intersections and increases them at 33% of intersections. Here, among potentially other factors relating to site-specific conditions and driver adaptation, there is the likely safety trade-off between reduced speeds and increasing speed variance. Because this parameter is random across intersections, at least the 5 mi/h speed-limit reduction there seems to be some ambiguity as to which of the two effects (decreasing mean speed or increasing speed variance) dominates overall safety performance. However, this ambiguity seems to be resolved at the 10 mi/h speed limit reduction level. For the 10 mi/h speed-limit reduction indicator, the parameter is fixed and negative indicating a decrease in approach crash frequencies. In fact, the marginal effects in Table 3 show that this decrease is reasonably large with 0.34 fewer crashes per year for approaches that had a 10 mi/h reduction in speed limits combined with signal-warning flashers.[5] This is an

[5] Given that the mean number of crashes at all intersection approaches is 1.13 crashes per year, 0.34 crashes per year constitutes a significant safety improvement.

important finding in that it clearly shows that speed limit reductions of at least 10 mi/h are needed to have an unambiguously positive effect on safety.[6]

METHODOLOGY – CRASH-INJURY SEVERITY

Discrete outcome models have been widely used to model crash injury-severity data. In this study, possible injury outcomes (the police-reported injury status of the most severely injured vehicle occupant in the crash) include: no injury, possible injury, visible injury, incapacitating injury, and fatality. To address this type of discrete outcome data, over the years researchers have used a variety of methodological approaches including ordered probability models, multinomial logit models, nested logit models, mixed (random parameters) logit models and dual-state multinomial logit models (Shankar et al., 1996; Duncan et al., 1998; Chang and Mannering, 1999; Khattak, 2001; Kockelman and Kweon, 2002; Abdel-Aty, 2003; Yamamoto and Shankar, Eluru et al., 2007; Savolainen and Mannering, 2007; Milton et al., 2008; Malyshkina and Mannering, 2009; Christoforou et al., 2010; Kim et al., 2010; Anastasopoulos and Mannering, 2011; Morgan and Mannering, 2011; Ye and Lord 2011; Patil et al., 2012). A complete review of crash-injury severity models and methodological approaches can be found in Savolainen et al. (2011). Studies have

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[6] There is the possibility that speed-limit reductions are more likely to be used at intersection approaches with high crash frequencies. If this is the case, in the presence of omitted variables and unobserved heterogeneity, the parameter estimates of the speed-limit reduction indicators will be estimated with a upward bias with regard to frequencies because the speed-limit indicators will be picking up unobserved factors that make these approaches more likely to have high crash frequencies. Our review of speed-limit placement policies, rich model specification, and significant negative parameter estimates for speed-limit reduction indicators suggest that the impact of this potentially non-random implementation of speed-limit reductions is likely to be minimal. However, in the worst case, our findings can be considered as a lower bound of the effectiveness of speed-limit reductions. Please see Carson and Mannering (2001) for a discussion of the non-random implementation of safety countermeasures with regard to the placement of ice-warning signs in Washington State.

shown that the choice of one methodological approach over another is often data dependent, although the parametric restrictions of the ordered probability models can preclude them as a feasible alternative (Savolainen et al., 2011).[7]

After extensive consideration of the standard multinomial logit, mixed logit and nested logit (Savolainen et al., 2011), the nested logit model provided the best overall statistical fit.[8] The nested logit model is a generalization of the standard multinomial logit model that overcomes the restriction that requires the assumption that the error terms are independently distributed across injury outcomes. As shown in past work, this independence may not always be the case if some crash-injury severity levels share unobserved effects (Savolainen and Mannering, 2007). For example, with the five injury categories we will consider in this paper (no injury, possible injury, visible injury, incapacitating injury and fatality), it is possible that adjacent injury-severity categories may share unobserved effects that relate to lower-impact collisions, thus violating the assumption that the error terms are independently distributed across outcomes, an assumption needed for the derivation of the standard multinomial logit model. The nested logit model deals with possible correlation of unobserved effects among discrete outcomes by grouping outcomes that share unobserved into conditional nests. The outcome probabilities are determined by

[7] As pointed out in Savolainen et al. (2011), ordered probability models are particularly susceptible to under-reporting of less severe crashes and such models place an often unrealistic restriction on the effect variables can have on crash-injury outcomes. This is because traditional ordered probability models cannot allow a variable to simultaneously decrease (or simultaneously increase) the probability of the lowest and highest severity levels (it should be noted that some recent work by Eluru et al. (2008) develops a generalized ordered probability model that relaxes the variable restriction of standard ordered probability models). See Savolainen et al. (2011), for further discussion of this point.

[8] The mixed logit model did not produce any statistically significant random parameters at the 95% confidence level (only one parameter was found to be significant even at the 90% confidence level). As will be shown, the standard multinomial logit could be statistically rejected relative to the nested logit model.

differences in the functions determining these probabilities with shared unobserved effects canceling out in each nest. The nested logit model has the following structure for crash n resulting in injury outcome i (see McFadden 1981, Washington et al., 2011)

$$P_n(j|i) = EXP[\boldsymbol{\beta}_{j|i}\mathbf{X}_{jn}] \Big/ \sum_{\forall J} EXP[\boldsymbol{\beta}_{J|i}\mathbf{X}_{Jn}] \tag{7}$$

$$LS_{in} = LN[\sum_{\forall J} \exp(\boldsymbol{\beta}_{J|i}\mathbf{X}_{Jn})] \ , \tag{8}$$

$$P_n(i) = EXP[\boldsymbol{\beta}_i\mathbf{X}_{in} + \phi_i \, \mathrm{LS}_{in}] \Big/ \sum_{\forall I} EXP[\boldsymbol{\beta}_I\mathbf{X}_{In} + \phi_I \, \mathrm{LS}_{In}] \tag{9}$$

where $P_n(i)$ is the unconditional probability of crash n having injury outcome i, $\mathbf{X}$'s are vectors of measurable characteristics that determine the probability of injury outcomes, $\boldsymbol{\beta}$'s are vectors of estimable parameters, and $P_n(j|i)$ is the probability of crash n having injury severity j conditioned on the injury severity being in injury-severity category i, J is the conditional set of outcomes (conditioned on i), I is the unconditional set of outcome categories, LS_{in} is the inclusive value (logsum), and ϕ_i is an estimable parameter.

For an example of a nested structure, consider a model that has correlation of unobserved effects among intermediate injury outcomes of possible injury and visible injury. In this case, in equation 9, the outcome categories i would include no injury, incapacitating injury, fatal injury, and a "lower intermediate injury" category (which would determine the unconditional probability of the crash resulting in a possible- or visible-injury outcome). The lower-intermediate-injury category ($P_n(i)$ in Equation 9) would include a LS_{in} as the inclusive value (logsum) which would be the denominator from the binary logit model estimated in Equation 7 with possible outcomes of possible injury and visible injury conditioned on the fact that the crash resulted in a lower-intermediate-injury category (that is, possible injury and visible injury). Visually this model structure is shown in Figure 1.

Estimation of a nested model logit model is readily undertaken using a full information maximum likelihood approach that ensures that variance-covariance matrices are properly estimated (this is in contrast to older sequential maximum likelihood estimation which underestimated the variance-covariance matrices resulting in an over estimation of the t-statistics of parameter estimates). We use this full information maximum likelihood approach in our model estimations (see Greene, 2007 for additional details).

In comparing nested and un-nested logit models, it is important to note that if the estimated value of ϕ_i is not significantly different from 1, the assumed shared unobserved effects in the lower-nest are not significant and the nested model reduces to a simple multinomial logit model (see Equations 8-9 with ϕ_i's = 1).

As was the case for the random-parameters negative binomial model, to assess the impact of specific variables on the crash severity probabilities, marginal effects are computed (see Washington et al., 2011). Again, marginal effects are computed for each observation and then averaged across all observations. The marginal effects give the impact that a one-unit change in an explanatory variable, x_i, has on the probability of crash injury-severity outcome i.

ESTIMATION RESULTS: INJURY SEVERITY

Table 4 shows the nested logit model estimation results and corresponding marginal effects are presented in Table 5. After multiple trials, the appropriate nested logit model formulation had a lower nest of lower-intermediate injuries (possible injury and visible injury) as depicted in Figure 1.[9] As shown in Table 4, the inclusive value (logsum) of the lower nest produced a parameter estimate of 0.24 with a standard error of 0.13 which gives a t-statistic of -5.85 ([β-1]/s.e.) showing that the logsum's parameter estimate is significantly different from one, validating the form of the nested logit relative to the standard multinomial logit and indicating the presence of shared unobserved effects in possible and visible injury-severity categories.[10]

As Tables 4 and 5 indicate, all parameter estimates are of plausible sign and magnitude (as reflected in the computed marginal effects). Turning specifically to the variables of interest (the speed-limit reduction indicators), it is found that the 5 mi/h speed limit reduction indicator was only found to be significant in the visible-injury outcome. Marginal effects in Table 5 show that a 5 mi/h speed-limit reduction reduces the probability of visible injury by 0.0831. This implies that the probability of other injury categories (no injury, possible injury, incapacitating injury, and fatality) all increase in the presence of a 5 mi/h speed-limit reduction.[11] As such, the net effect of

[9] This is in contrast to the earlier work of Savolainen and Mannering (2007) which, in their analysis of motorcycle-rider injuries, found the lowest injury-severity categories shared unobserved effects as opposed to the intermediate categories. This and other research suggests appropriate nesting structures tend to be quite data-specific in the case of injury-severity analyses.

[10] Recall an inclusive value that is not significantly different from one indicates that the model reduces to the standard multinomial logit model. It is also noteworthy that the inclusive value parameter is between zero and one, which is the range needed for model validity (McFadden, 1981).

[11] Note that the finding that the fact that the 5 mi/ speed-limit reduction indicator was found to be significant only for the visible-injury outcome (an intermediate severity outcome) is a further indication that an ordered probability model of crash-severity outcomes is not appropriate for these data. This is because ordered probability model structures (such as the standard ordered probit model) do not allow for the possibility of variables influencing only

a 5 mi/h speed-limit reduction on crash severity is ambiguous because it reduces the probability of visible injury, but increases the probability of other less severe and more severe crash-injury outcomes.

In contrast, the effect of the 10 mi/h reduction in speed limit (whose indicator variable was found to be only significant in the no-injury outcome) has an unambiguous effect in that it increases the probability of a no-injury crash by a substantial 0.196 and thus simultaneously decreases the probability of all of the more severe injury outcomes (visible injury, possible injury, incapacitating injury, and fatality).[12]

These injury-severity findings corroborate the findings in the crash-frequency model where it was found that the effect of a 5 mi/h speed-limit reduction was also ambiguous – reducing crash frequencies on 67% of the intersection approaches while increase crash frequencies on 33% of the intersection approaches. A likely explanation for this consistent finding is that the increase in speed variance caused by the speed limit reduction can sometimes exceed the potential benefits from the lower speed limits providing smaller distances covered during reaction times (allowing a higher likelihood of crash avoidance) and the lower energy-impact crashes – as appears to be the case for a 5 mi/h speed-limit reduction. However, for a 10 mi/h reduction in the speed limit, the resulting increase in speed variance is overcome by the smaller distance travelled during reaction

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intermediate outcomes. That is, they do not allow for the possibility that a variable can simultaneously decrease or simultaneously increase the extreme outcomes as is the case here – where the 5 mi/h speed reduction indicator simultaneously increases the probability of no injury and fatality crashes.

[12] Along the lines of the discussion in footnote 6, there is the possibility that speed-limit reduction may be more likely to be implemented at intersection approaches with a history of severe crashes. This would again be problematic in the presence of omitted variables and unobserved heterogeneity with the result being that parameter estimates for speed-limit indicators would underestimate their ability to mitigate severe crashes. We again find no evidence for the presence of this bias but our results could be viewed as a lower bound of the effectiveness of speed-limit reductions.

and the energy reduction afforded by the lower speeds – resulting in a clear reduction in both the frequency and severity of crashes.

SUMMARY AND CONCLUSIONS

This study provides an empirical assessment of safety impacts associated with implementing reduced speed limits in the vicinity of signalized high-speed intersections equipped with signal-warning flashers. The analysis was performed to identify the effects of speed-limit reductions on crash frequency and severity while considering various roadway geometric, traffic-control and traffic-flow characteristics. Ten-year crash data from 28 intersections in Nebraska (all with intersection approaches having signal-warning flashers and some having either a 5 mi/h or 10 mi/h reduction in speed limit) were used to estimate appropriate crash frequency and severity models.

The estimation results show, in terms of crash frequency, a 5 mi/h speed-limit reduction has an ambiguous effect on the frequency of crashes – decreasing crash frequency on 67% of the intersection approaches and increasing it on 33% of the intersection approaches. In contrast, a 10 mi/h speed-limit reduction was shown to unambiguously decrease the frequency of crashes. Crash-severity models produced similar findings, with 5 mi/h crashes increasing the likelihood of both very minor and very severe crashes (thus making the net safety benefits ambiguous) and 10 mi/h crashes unambiguously reducing the probability of more severe crashes (from possible injury all the way to fatal crashes). As discussed in the text, this finding is likely the result of the fact that the smaller distances covered during reaction times (allowing a higher likelihood of crash avoidance) and reduce the energy of crashes associate with lower speed limits are not necessarily sufficient to overcome the increased speed variance caused by a speed-limit reduction in the 5 mi/h speed-limit reduction case – but they are sufficient to overcome the increased speed variance

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caused by a speed-limit reduction in the 10 mi/h speed-limit reduction case. Thus the findings of this research are clear – speed limit reductions in conjunction with signal-warning flasher are an effective safety countermeasure, but only clearly so if the speed-limit reduction is 10 mi/h.[13]

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References

Abdel-Aty, M. A., 2003. Analysis of driver injury severity levels at multiple locations using ordered probit models. Journal of Safety Research 34(5), 597-603.

Anastasopoulos, P., Mannering, F., 2009. A note on modeling vehicle accident frequencies with random-parameters count models. Accident Analysis and Prevention 41 (1), 153-159.

Anastasopoulos, P., Mannering, F., 2011. An empirical assessment of fixed and random parameter logit models using crash- and non-crash specific injury data. Accident Analysis and Prevention

[13] The data used in this study only included speed-limit reductions of 5 and 10 mi/h. A fruitful area for further research would be to consider the effect of higher speed-limit reductions.

43 (3), 1140-1147.

Antonucci, N., Pfefer, R., Neuman, T., 2004. National cooperative highway research program (NCHRP) report 500 volume 12: a guide for reducing collisions at signalized intersections, Transportation Research Board. Washington, D.C., p. I1-I4.

Appiah, J., Naik, B., Wojtal, R., Rilett, L., 2011. Safety effectiveness of actuated advance warning systems. Transportation Research Record 2250, 19-24.

Boyle, L., Mannering, F., 2004. Impact of traveler advisory systems on driving speed: Some new evidence. Transportation Research Part C 12(1), 57-72.

Buddemeyer, J., Young, R., Dorsey-Spitz, B., 2010. Rural variable speed limit system for southeast Wyoming. Transportation Research Record 2189, 37-44.

Burnett, N., Sharma, A., 2011. Role of information on probability of traffic conflict on the onset of yellow. Advances in Transportation Studies an International Journal RSS2011 Special Issue, 29-40.

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.

Christoforou, Z., Cohen, S., Karlaftis, M., 2010. Vehicle occupant injury severity on highways: an empirical investigation. Accident Analysis and Prevention 42(6), 1606-1620.

Cruzado, I., Donnell E., 2010. Factors affecting driver speed choice along two-lane rural highway transition zones. Journal of Transportation Engineering 136 (8), 755-764.

Duncan C., Khattak, A., Council, F., 1998. Applying the ordered probit model to injury severity in truck-passenger car rear-end collisions. Transportation Research Record, 1635, 63-71.

Eluru, N., Bhat, C., Hensher, D., 2008. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. Accident Analysis and Prevention 40(3), 1033-1054.

Federal Highway Administration, 2009. Manual on uniform traffic control devices for streets and highways (MUTCD). FHWA and U.S. Department of Transportation. Retrieved from mucd.fhwa.gov.

Greene,W., 2007. Limdep, Version 9.0. Econometric Software, Inc., Plainview, NY.

Institute of Transportation Engineers, 1985. Recommended practice: Determining vehicle change intervals. Technical Committee 4A-16, Washington, D.C.

Khattak, A., 2001. Injury severity in multi-vehicle rear-end crashes. Transportation Research Record 1746, 59-68.

Kim, J.-K., Ulfarsson, G., Shankar, V., Mannering, F., 2010. A note on modeling pedestrian-injury severity in motor-vehicle crashes with the mixed logit model. Accident Analysis and Prevention 42 (6), 1751-1758.

Kockelman, K., Kweon, Y.-J., 2002. Driver injury severity: An application of ordered probit models. Accident Analysis and Prevention 34(4), 313-321.

Lee, J., Mannering, F., 2002. Impact of roadside features on the frequency and severity of run–

off–roadway accidents: An empirical analysis. Accident Analysis and Prevention 34(2), 149-161.

Lord, D., Mannering, F., 2010. The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives. Transportation Research Part A 44 (5), 291-305.

Malyshkina, N., Mannering, F., 2008. Effect of increases in speed limit on severities of injuries in accidents. Transportation Research Record 2083, 122-127

Malyshkina, N., Mannering, F., 2009. Markov switching multinomial logit model: An application to accident-injury severities. Accident Analysis and Prevention 41(4), 829-838.

McFadden, D. 1981. Econometric models of probabilistic choice. Structure Analysis of Discrete Data with Econometric Applications. Edited by C.F. Manski and D. McFadden. Cambridge, MA: MIT Press.

Milton, J., Shankar, V., Mannering, F., 2008. Highway accident severities and the mixed logit model: an exploratory empirical analysis. Accident Analysis and Prevention 40 (1), 260-266.

Monsere, C., Nolan, C., Bertini, R., Anderson, E., El-Seoud, T., 2005. Measuring the impacts of speed reduction technologies: a dynamic advanced curve warning system evaluation. In: Proceedings of the 84th Annual Meeting of the Transportation Research Board, Washington, D.C.

Morgan, A., Mannering, F., 2011. The effects of road-surface conditions, age, and gender on diver-injury severities. Accident Analysis and Prevention 43 (5), 1852-1863.

National Highway Traffic Safety Administration (2012). Traffic safety facts research note.

http://www-nrd.nhtsa.dot.gov/Pubs/811552.pdf, accessed on Sep 12, 2012.

Parker., M., 1997. Effects of raising and lowering speed limits on selected roadway sections. U.S. Department of Transportation Publication, McLean, Virginia.

Patil, S., Greedipally, R., Lord, D., 2012. Analysis of crash severities using nested logit model – Accounting for underreporting of crashes. Accident Analysis and Prevention 45, 646-653.

Poch, M., Mannering, F., 1996. Negative binomial analysis of intersection-accident frequencies. Journal of Transportation Engineering 122(2), 105-113.

Savolainen, P., Mannering, F., 2007. Probabilistic models of motorcyclists' injury severities in single- and multi-vehicle crashes. Accident Analysis and Prevention 39 (5), 955-963.

Savolainen, P., Mannering, F., Lord, D., Quddus, M., 2011. The statistical analysis of highway crash-injury severities: a review and assessment of methodological alternatives. Accident Analysis and Prevention 43 (5), 1666-1676.

Shankar, V., Mannering, F., and Barfield, W., 1996. Statistical analysis of accident severity on rural freeways. Accident Analysis and Prevention 28(3), 391-401.

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

Son, H., Fontaine, M., Park, B., 2009. Long-term speed compliance and safety impacts of rational speed limits. Journal of Transportation Engineering 135 (8), 536-545.

Towliat, M., Svensson, H., Lind, G., Lindkvist, A., 2006. Variable speed limits at intersections-effects and experience. In: Proceedings of European Transportation Conference 2006.

van den Hoogen, E., Smulders, S., 1994. Control by variable speed signs: results of the Dutch experiment. In: Proceedings of the 7th International Conference Road Traffic Monitoring and Control, pp.145-149.

Washington, S., Karlaftis, M., Mannering, F., 2011. Statistical and Econometric Methods for Transportation Data Analysis, Second Edition. Chapman and Hall/CRC.

Wu, Z., Sharma, A., Wang, S.. 2012. Evaluation of effectiveness of speed limit reductions at high-speed intersections with advance warning flasher. Accepted for presentation in the 92nd Annual Meeting of the Transportation Research Board, Washington, D.C.

Yamamoto, T. , Shankar, V., 2004. Bivariate ordered-response probit model of driver's and passenger's injury severities in collisions with fixed objects, Accident Analysis and Prevention 36(5), 869-876.

Ye, F., Lord, D., 2011. Comparing three commonly used crash severity models on sample size requirements: multinomial logit, ordered probit and mixed logit models. In: Proceedings of the 90th Annual Meeting of the Transportation Research Board, Washington, D.C.

Table 1. Descriptive statistics of crash-related variables.

Variables	**Value**
Average annual crash frequency on intersection approaches (Std. Dev.)	1.13 (1.42)
Average percentage of truck volume on intersection approaches (Std. Dev.)	7.69 (6.15)
Average daily travel in vehicles per lane on intersection approaches (Std. Dev.)	1851.95 (911.28)
Percentage of intersection approaches with divided medians	83.21
Percentage of intersection approaches with a 5 mi/h reduction in speed limit	16.79
Percentage of intersection approaches with a 10 mi/h reduction in speed limit	7.46

Percentage of intersection approaches with exclusive left turn lanes	94.48
Percentage of intersection approaches with sufficient yellow time. Yellow time is sufficient if the actual yellow time is greater than the suggested yellow time which is calculated as $t_r + S_{85}/2a(64.4*0.01G)$, where t_r is the standard assumed reaction time (2.5 seconds), S_{85} is the 85% percentile of speed in ft/s, a is the standard assumed vehicle deceleration (11.2 ft/s^2) and G is the grade in percent. See (Institute of Transportation Engineers,1985; Mannering and Washburn, 2013).	33.58
Percentage of intersection approaches with an insufficient flasher time. Flasher time is insufficient if actual flasher time is less than the time required for the drivers driving at signal-approach speed limit traveling from the flasher to the stop line (time required is the distance to the stop line in feet divided by the speed limit of the approach in ft/s.	70.15
Average age of at-fault driver (Std. Dev.)	40.43 (19.71)
Percentage of at-fault drivers that were male	63.94
Percentage of at-fault drivers that had been using alcohol	2.52
Percentage of crashes involving three or more vehicles	7.56
Percentage of crashes classified as out-of-control crashes	5.2
Percentage of crashes classified as angle crashes	60.78
Percentage of crashes classified as head-on crashes	3.94
Percentage of crashes classified as rear-end crashes	30.08
Percentage of crashes classified property damage only crashes	45.36
Percentage of crashes classified possible-injury crashes	24.72
Percentage of crashes classified visible-injury crashes	18.74
Percentage of crashes classified incapacitating injury crashes	9.92
Percentage of crashes classified fatality crashes	1.26

Table 2. Model estimation results for random parameters negative binomial model of intersection crash frequency (all random parameters are normally distributed).

Variable	Parameter Estimate	t-stat
Constant	-1.91	-7.74
Truck percentage	0.0193	2.07
Average daily travel per lane (in thousands of vehicles)	0.33	5.51
Divided median indicator (1 if intersection approach has a divided median, 0 otherwise)	1.11	7.24
Insufficient flasher-time indicator (1 if the actual flasher time is less than the time required for the drivers driving at signal-approach speed limit traveling from the flasher to the stop line, 0 otherwise)	0.14	1.31
(*Standard deviation of parameter distribution*)	(*0.80*)	(*10.99*)
Sufficient yellow time indicator (1 if the actual yellow time is greater than the suggested yellow time, 0 otherwise; see Table 1 for definition)	-0.09	-0.77
(*Standard deviation of parameter distribution*)	(*0.70*)	(*6.86*)
Percentage of approach traffic making left turns	-0.51	-1.20
(*Standard deviation of parameter distribution*)	(*2.31*)	(*6.67*)
5 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 5 mi/h, 0 otherwise)	-0.32	-2.24
(*Standard deviation of parameter distribution*)	(*0.72*)	(*4.91*)
10 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 10 mi/h, 0 otherwise)	-0.47	-2.00
Dispersion parameter, α	8.19	1.98
Number of observations	536	
Log-likelihood with constant only	-1104.00	
Log-likelihood at convergence	-732.05	

Table 3. Marginal effects for explanatory variables in the random parameters negative binomial of intersection crash frequency.

Variables	Average Marginal effect	Standard Deviation
Truck percentage	0.0142	0.00689
Average daily travel per lane (in thousands of vehicles)	0.24	0.043
Divided median indicator (1 if intersection approach has a divided median, 0 otherwise)	0.81	0.111
Insufficient flasher-time indicator (1 if the actual flasher time is less than the time required for the drivers driving at signal-approach speed limit traveling from the flasher to the stop line, 0 otherwise)	0.10	0.769
Sufficient yellow time indicator (1 if the actual yellow time is greater than the suggested yellow time 0 otherwise; see Table 1 for definition)	-0.06	0.078
Percentage of approach traffic making left turns	-0.0037	0.0031
5 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 5 mi/h, 0 otherwise)	-0.23	0.097
10 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 10 mi/h, 0 otherwise)	-0.34	0.170

Table 4. Nested logit model for crash severity at high speed signalized intersections. Severity levels (see Figure 1): NI=no injury(upper nest); PI=Possible Injury (lower nest), VI=Visible Injury (lower nest), INI=Incapacitating Injury (upper nest), F=Fatality (upper nest), LII=Lower Intermediate Injury (upper nest).

Severity Level	**Variable**	**Parameter Estimate**	**t-stat**
Lower nest			
PI	Rear-end crash indicator (1 if the crash was a rear-end crash, 0 otherwise)	2.12	4.09
	Left-turn lane indicator (1 if left-turn lane is present on the intersection approach, 0 otherwise)	1.20	2.01
VI	Constant	1.79	2.04
	5 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 10 mi/h, 0 otherwise)	-0.96	-2.10
	Truck percentage	-6.01	-2.02
	Average daily travel per lane (in thousands of vehicles)	0.44	2.47
	At-fault driver-age indicator (1 if the at-fault driver was more than 60 years old, 0 otherwise)	0.77	2.21
	At-fault male-driver indicator (1 if the at-fault driver was male, 0 otherwise)	-0.52	-1.90
	Angle crash indicator (1 if the crash was an angle crash, 0 otherwise)	-0.85	-1.76
Upper nest			
NI	Constant	1.07	2.34
	Head-on indicator (1 if the crash was head-on crash, 0 otherwise)	-1.19	-2.46
	Divided median indicator (1 if intersection approach has a divided median, 0 otherwise)	-2.10	-2.80
	Sufficient yellow time indicator (1 if the actual yellow time is greater than the suggested yellow time 0 otherwise; see Table 1 for definition)	0.67	3.56
	10 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 10 mi/h, 0 otherwise)	0.85	2.38
	Multiple-vehicle indicator (1 if crash involved more than two vehicles, 0 otherwise)	-1.14	-3.24
LII	Percentage of approach traffic making left turns	-1.25	-1.70
	Divided median indicator (1 if intersection approach has a divided median, 0 otherwise)	-1.23	-1.63
	Inclusive value (logsum)	*0.24*	*-5.85**

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InI	Constant	-3.27	-3.63
	At-fault driver drinking indicator (1 if the at-fault driver had been drinking, 0 otherwise)	1.91	3.27
	Angle crash indicator (1 if the crash was an angle crash, 0 otherwise)	1.34	3.50
F	Constant	-2.02	-1.61
	Average daily travel per lane (in thousands of vehicles)	-1.49	-2.23
	Indicator variable: At-fault driver had been drinking	2.06	1.80
Number of Observations		635	
Log-likelihood at zero, LL(0)		-1071.61	
Log-likelihood at convergence, LL(β)		-753.51	
McFadden ρ^2 (1-LL(β)/LL(0))		0.30	

* As opposed to all other t-statistics which are computed as β – 0 (since we are interested in whether the parameter is significantly different from zero) divided by the standard error, the inclusive value t-statistic is computed as β – 1 divided by the standard error, since the statistical difference from 1 indicates whether the nested structure is valid as opposed to a traditional multinomial logit.

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Table 5. Marginal effects of the nested logit model for crash severity at high speed signalized intersections. Severity levels (see Figure 1): NI=no injury(upper nest); PI=Possible Injury (lower nest), VI=Visible Injury (lower nest), INI=Incapacitating Injury (upper nest), F=Fatality (upper nest), LII=Lower Intermediate Injury (upper nest).

Variable	NI	PI	VI	INI	F	LII
Traffic-flow characteristics						
Truck Percentage			-0.0052			-0.000724
Average daily travel per lane (in thousands of vehicles)			0.0383		0.0181	0.0048
Traffic-control characteristics						
5 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 10 mi/h, 0 otherwise)			-0.0831			-0.0116
10 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 10 mi/h, 0 otherwise)	0.196					
Sufficient yellow time indicator (1 if the actual yellow time is greater than the suggested yellow time 0 otherwise; see Table 1 for definition)	0.154					
Divided median indicator (1 if intersection approach has a divided median, 0 otherwise)	-0.486					
Left-turn lane indicator (1 if left-turn lane is present on the intersection approach, 0 otherwise)		0.104				0.024
Driver Characteristics						
At-fault driver-age indicator (1 if the at-fault driver was more than 60 years old, 0 otherwise)			0.067			0.0092
At-fault male-driver indicator (1 if the at-fault driver was male, 0 otherwise)			-0.045			-0.0063
At-fault driver drinking indicator (1 if the at-fault driver had been drinking, 0 otherwise)				0.160	0.025	
Crash Characteristics						
Angle crash indicator (1 if the crash was an angle crash, 0 otherwise)			-0.073	0.112		-0.010
Head-on indicator (1 if the crash was head-on crash, 0 otherwise)	-0.276					

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Rear-end crash		0.184	0.043
Multiple-vehicle indicator (1 if crash involved more than two vehicles, 0 otherwise)	-0.265		

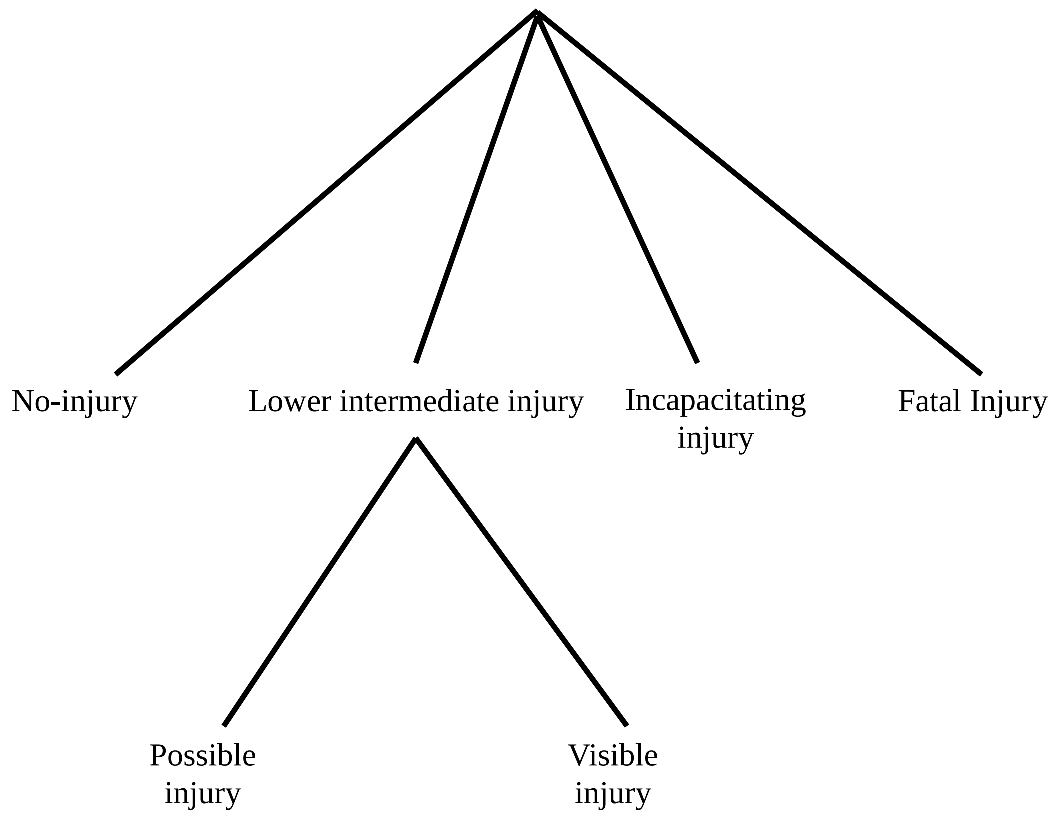

Figure 1: Nested logit structure of the crash-injury severity model.