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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, in the presence of potentially heterogeneous driver responses to decreased speed limits, the smaller distances covered during reaction time at lower speeds (allowing a higher likelihood of crash avoidance) and the reduced energy of crashes associated with lower speed limits are not necessarily sufficient to unambiguously decrease the frequency and severity of crashes when the speed-limit reduction is just 5 mi/h. However, they are sufficient to unambiguously decrease the frequency and severity of crashes when the speed-limit reduction is 10 mi/h. 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.

1. Introduction

Traffic-safety data indicate that greater than 20% of all traffic fatalities in the United States occur at intersections. In 2010 alone, more than 6700 fatalities occurred at intersections in the U.S. (National Highway Traffic Safety Administration, 2012). While many factors determine the likelihood of intersection crashes in general, and fatal crashes in particular, 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 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 low compliance. However, a speed reduction for certain special cases, such as 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

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than the reduction of the posted speed limit. In addition, lowering the speed limit does not always improve safety because the speed-limit reduction may be too modest for the larger crash-avoidance distances available to drivers and the reduced impact energies of lower-speed crashes to have a significant effect on the frequency and severity of crashes. Also, there is the possibility that some drivers may continue to travel at a speed that they perceive to be reasonable and safe while others may attempt to comply with the reduced posted speed limit—resulting in an increase in speed variance that can completely offset the benefits of the reduced speed limit or in some cases actually result in more dangerous traffic conditions. 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 also sped up when the adverse conditions passed, to make up for lost time, causing high variances in speed during and after the hazard. And, in other work, Malyshkina and Mannering (2008) found that increasing speed limits on interstate highways by 5 mi/h in Indiana did not result in an increase in crash-injury severities, partly because of the decline in speed variance at the higher speed limit.

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% 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 of speed-limit reductions and signal-warning flashers at high-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 Traffic Control Devices (Federal Highway Administration, 2009). In contrast, guidelines for implementing speed-limit reductions at high-speed intersections do not exist, and states may not apply reductions unless there are significant intersection-related safety concerns, such as a history of frequent and/or severe-injury crashes or sight-distance restrictions.

The presence of signal-warning flashers further complicates the issue surrounding the necessity and effectiveness of speed-limit reductions, and 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 driver 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 net effect of both of these countermeasures may be compromised.[1] This paper will investigate the safety effects of speed-limit reductions at high-speed signalized intersections with signal-warning flashers, by considering their effects on crash frequencies and severities.

2. Empirical setting

The crash dataset available for this study consists of crash data from 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 on the primary highways (the higher volume highways) 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 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. Here, 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.

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 dataset includes detailed police-reported crash data from 635 crashes that occurred during the study period. Each crash was documented together with 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 the variables found to be significant in forthcoming crash frequency and crash severity models are provided in Table 1.

In Table 1, for the percentage of intersections with sufficient yellow time, yellow time is considered sufficient if the actual yellow time is greater than the suggested yellow time which is calculated as $t_r + S_{85}/(2a + 0.644G)$, where t_r is the standard assumed perception-reaction time (1 s), S_{85} is the 85th 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). Also, for the percentage of intersection approaches with an insufficient signal-warning flasher time, flasher time is considered 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

[1] One key effect here is the possibility that the heterogeneous driver compliance will result in an increase in speed variance. However, this does not appear to be the case. For example, Wu et al. (2013) showed, by considering vehicle speeds before the speed-limit reduction and after, 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 (based on speed data collected from some of the same intersection approaches considered in the current paper) reduced mean operating speeds by 3.8 mi/h without significantly changing the standard deviation of speeds.

Table 1
Descriptive statistics of crash-related variables.[a]

Variable	Value
Crash-frequency data	
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 (6.12)
Average daily travel in vehicles per lane on intersection approaches (std. dev.)	1851.95 (911.29)
Average percentage of left-turn volume on intersection approaches (std. dev)	12.63 (13.79)
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 sufficient yellow time (see text for definition).	33.58
Percentage of intersection approaches with an insufficient signal-warning flasher time (see text for definition)	70.15
Crash-severity data	
Average daily travel in vehicles per lane on intersection approaches (std. dev.)	2028.43 (921.38)
Average percentage of truck volume on intersection approaches (std. dev.)	7.42 (6.40)
Average percentage of left-turn volume on intersection approaches (std. dev.)	11.14 (11.99)
Percentage of intersection approaches with divided medians	87.87
Percentage of intersection approaches with a 5 mi/h reduction in speed limit	13.86
Percentage of intersection approaches with a 10 mi/h reduction in speed limit	5.98
Percentage of intersection approaches with an insufficient flasher time	26.78
Percentage of intersection approaches with exclusive left turn lanes	94.49
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 as property damage only crashes	45.36
Percentage of crashes classified as possible-injury crashes	24.72
Percentage of crashes classified as visible-injury crashes	18.74
Percentage of crashes classified as incapacitating injury crashes	9.92
Percentage of crashes classified as fatality crashes	1.26

[a] Variables will have different values in the crash-frequency and crash-severity data because the units of observation are different. In the crash-frequency case the number of crashes on individual intersection approaches (the unit of observation) is considered, whereas in crash severity each individual crash (the unit of observation) is considered. Substantial differences in the approach-specific values (such as traffic volume, speed-limit reductions, etc.) between the two data bases reflect the fact that the number of individual crashes occurring on specific approaches can substantially change values in the injury-severity data since high crash-frequency approaches will be over represented and low crash-frequency approaches will be under represented (this is in contrast to the crash-frequency where each approach has "equal" representation with one value per approach per year).

(time required is the distance to the stop line in feet divided by the speed limit of the approach in ft/s).

3. Methodology

To assess the safety impacts of signal-warning flashers and speed control at high-speed signalized intersections, consideration will be given to the frequency of crashes and then to the severity of crashes once a crash has occurred. Turning first to the analysis of crash frequency, count-data modeling techniques have been shown to be an appropriate methodological approach because the number of crashes assigned to an intersection approach is a non-negative integer (see Lord and Mannering, 2010). 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; Lee and Mannering, 2002; 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,

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

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 the 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 ($E[n_i] \ll VAR[n_i]$) 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 $\Gamma(.)$ is a gamma function. Note 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 (note that, with ten years of data and typically two of the four intersection approaches having the signal-warning flashers, a typical intersection generates 20 observations). This is in contrast to the traditional random parameters approach where each observation (in this case each year/intersection-approach combination) would get their own β. The advantage of having a single parameter for the approaches in the same intersection (as opposed to allowing each approach to have its own parameter) is that the model takes into account additional information (the fact that the approaches are from the same intersection and thus are likely to share many of the same unobserved effects). This additional information is traded off against the restriction being placed on the parameters (that they are constrained to be the same for each intersection approach in a given intersection). Subsequent model estimations clearly show that constraining the approach parameters to be the same for each intersection is statistically justified.[2] 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 Eq. (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 Eq. (4)). The log-likelihood function for the random parameters negative binomial in this case can be written as,

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

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

Because maximum likelihood estimation of the random-parameters 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.

With regard to the injury-severity of crashes given that a crash has occurred, discrete outcome models have been widely used. 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, dual-state multinomial logit models and finite-mixture random-parameter 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, 2004; Eluru et al., 2008; 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; Xiong and Mannering, 2013). A review of crash-injury severity models and methodological approaches can be found in Savolainen et al. (2011). Studies have 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).[3]

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 in current study.[4] 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 that we will consider in this paper (no injury, possible injury, visible injury, incapacitating injury and fatality),[5] 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 (see McFadden, 1981). The nested logit model deals with possible correlation of unobserved effects among discrete outcomes by grouping outcomes that share unobserved effects into conditional nests. The outcome probabilities are determined by 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):

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

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

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

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

[2] The model estimation that constrained the parameters of approaches in the same intersection to be identical had a log-likelihood at convergence ($LL(\boldsymbol{\beta}_{intersection})$) of −732.05 whereas the model that allowed all approaches to have their own parameter converged at ($\boldsymbol{\beta}_{approach}$) −760.67. The substantially higher value of $LL(\boldsymbol{\beta}_{intersection})$, clearly suggests that constraining the parameters of approaches on the same intersection to be identical provides a superior statistical fit.

[3] 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.

[4] 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.

[5] These severity levels follow the traditional "KABCO" scale: fatal injury or killed (K), incapacitating injury (A), non-incapacitating (B), possible injury (C), and property damage only (O).

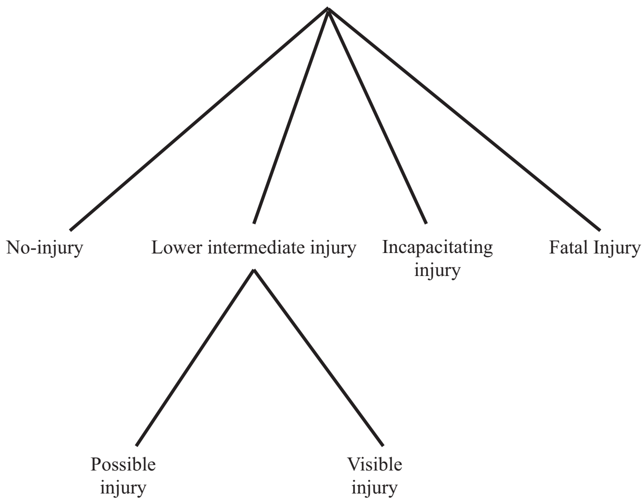

Fig. 1. Nested logit structure of the crash-injury severity model.

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 the intermediate injury outcomes of possible injury and visible injury. In this case, in Eq. (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 Eq. (9)) would include a LS_{in} as the inclusive value (logsum) which would be the denominator from the binary logit model estimated in Eq. (7) (as shown in Eq. (8)) 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 Fig. 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 approach which underestimated the variance–covariance matrices resulting in an over estimation of the t-statistics of parameter estimates, 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 Eqs. (8) and (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 for each observation and then averaged across all observations (see Washington et al., 2011). Here, 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.

4. Estimation results: crash frequency

The parameter estimation results and the corresponding average marginal effects are shown in Table 2. Table 2 shows that the random-parameters negative binomial model estimation 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 to the log-likelihood with only the constant included in the model (−1104.04). The random parameter model estimated is also superior to the simple fixed parameter model which produced a much lower log-likelihood at convergence of −797.77. Finally, 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 that the poorer braking performance of trucks can be expected to be problematic at high-speed intersections. The marginal effects in Table 2 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 the traffic volume per lane increase the frequency of crashes on intersection approaches. Here, marginal effects show that an increase in average traffic volume of 1000 vehicles per day per lane will increase the expected number of crashes by 0.24 per year (see Table 2). 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 frequencies with marginal effects showing that a divided-median intersection approach has a 0.81 higher annual crash frequency relative to undivided median approaches. Here, the median space between opposing approaches is likely causing a problem by increasing the time required for left-turning vehicles, and vehicles traveling through the intersection on the minor road, to cross the approach lanes and median to clear the intersection. Sight distance may also be an issue with divided medians in some cases.

The estimated parameter for the insufficient signal-warning flasher-time indicator (see earlier 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 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 signal-warning flasher times varies considerably among intersection approaches and this may be due to, among other factors, 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 signal-warning flashing times in different ways and this would explain the plus/minus variation in this parameter estimate.

The sufficient yellow-time indicator (see earlier 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 55% of the time and increased crash frequencies 45% 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 with a 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.

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.	Average marginal effect
Constant	−1.91	−7.74	
Truck percentage	0.0193	2.07	0.0142
Average daily travel per lane (in thousands of vehicles)	0.33	5.51	0.24
Divided median indicator (1 if intersection approach has a divided median, 0 otherwise)	1.11	7.24	0.81
Insufficient signal-warning flasher-time indicator (1 if the actual signal-warning 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) (*standard deviation of parameter distribution*)	0.14 (*0.80*)	1.31 (*10.99*)	0.10
Sufficient yellow time indicator (1 if the actual yellow time is greater than the suggested yellow time, 0 otherwise; see text for definition) (*standard deviation of parameter distribution*)	−0.09 (*0.70*)	−0.77 (*6.86*)	−0.06
Percentage of approach traffic making left turns (*standard deviation of parameter distribution*)	−0.0051(*0.0231*)	−1.20 (*6.67*)	−0.0037
5 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 5 mi/h, 0 otherwise) (*standard deviation of parameter distribution*)	−0.32 (*0.72*)	−2.24 (*4.91*)	−0.23
10 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 10 mi/h, 0 otherwise)	−0.47	−2.00	−0.34
Dispersion parameter, α	8.19	1.98	
Number of observations		536	
Log-likelihood with constant only		−1104.04	
Log-likelihood at convergence		−732.05	

Turning now to the specific variables of interest, the effect of various reductions in speed limit in the presence of signal-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, there is the possibility that the 5 mi/h speed-limit reduction is simply not sufficiently large enough to unambiguously decrease the

Table 3
Nested logit model for crash severity at high speed signalized intersections. Severity levels (see Fig. 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), and 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 5 mi/h, 0 otherwise)	−0.96	−2.10
	Truck percentage	−0.060	−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	−1.77
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	−0.0125	−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*[a]
InI	Constant	−3.28	−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
	At-fault driver drinking indicator (1 if the at-fault driver had been drinking, 0 otherwise)	2.06	1.80
Number of observations		635	
Log-likelihood at zero, $LL(0)$		−1071.61	
Log-likelihood at convergence, $LL(\beta)$		−753.51	
McFadden ρ^2 $(1 - LL(\beta)/LL(0))$		0.30	

[a] As opposed to all other t-statistics which are computed as $\beta - 0$ (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 $\beta - 1$ 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.

Table 4
Average marginal effects of the nested logit model for crash severity at high speed signalized intersections. Severity levels (see Fig. 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), and 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	0.0053
Traffic-control characteristics						
5 mi/h speed-limit reduction indicator (1 if speed limit is reduced by 5 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 text 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			0.0093
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					
Rear-end crash indicator (1 if the crash was a rear-end crash, 0 otherwise)		0.184				0.043
Multiple-vehicle indicator (1 if crash involved more than two vehicles, 0 otherwise)	−0.265					

frequency of crashes. That is, in the presence of potentially heterogeneous driver responses to decreased speed limits, the benefits drivers accrue from lower speeds (smaller distances covered during reaction time, which allow a higher likelihood of crash avoidance), at the 5 mi/h speed-limit reduction level, are not necessarily sufficient to unambiguously decrease the frequency of crashes.[6] 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 (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). This is an 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.[7]

5. Estimation results: injury severity

Table 3 shows the nested logit model estimation results and the corresponding marginal effects are presented in Table 4. 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 Fig. 1.[8] As shown in Table 3, 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 ($[\beta - 1]$/s.e.) showing that the logsum's parameter estimate is significantly different from one, thus validating the form of the nested logit relative to the standard multinomial logit and indicating the presence of shared unobserved effects between possible and visible injury-severity categories.[9]

As Tables 3 and 4 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), the 5 mi/h speed limit reduction indicator was only found to be significant in the visible-injury outcome. Marginal effects in Table 4 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.[10] As such, the net effect of 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

[6] The possible increase in speed variance caused by the reduction in speed limit could also be playing a role here in that the crash-avoidance benefits caused by lower speeds are being partially offset by increasing speed variances (making crashes more likely). However, as discussed in footnote 1, increasing speed variance is not statistically supported for the intersections in our sample for which speed data were collected (Wu et al., 2013).

[7] 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.

[8] 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.

[9] 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).

[10] Note that the fact that the 5 mi/h 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 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.

no-injury outcome) has an unambiguous effect in that it increases the probability of a no-injury crash by a substantial 0.196 (as shown in Table 4) and thus simultaneously decreases the probability of all of the more severe injury outcomes (visible injury, possible injury, incapacitating injury, and fatality).[11]

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 increasing crash frequencies on 33% of the intersection approaches.

Again, it is speculated that, in the presence of potentially heterogeneous driver responses to decreased speed limits, the larger distances covered during reaction time at lower speeds (allowing a higher likelihood of crash avoidance) and the reduced energy of crashes associated with lower speed limits (and the lower speeds at impact due to the additional reaction-time distance provided) are not necessarily sufficient to unambiguously decrease the frequency and severity of crashes when the speed-limit reduction is just 5 mi/h. However, they are sufficient to unambiguously decrease the frequency and severity of crashes when the speed-limit reduction is 10 mi/h.

6. Summary and conclusions

This study provides an empirical assessment of the 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 5 mi/h or 10 mi/h reductions in highway 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—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 speed-limit reductions increasing the likelihood of both very minor and very severe crashes (thus making the net safety benefits ambiguous) and with 10 mi/h speed-limit reductions unambiguously reducing the probability of more severe crashes (from crashes with severities of possible injury all the way up to fatal crashes). As discussed in the text, this finding is likely the result of the fact that, in the presence of potentially heterogeneous driver responses to decreased speed limits, the smaller distances covered during reaction times (allowing a higher likelihood of crash avoidance) and the reduced energy of crashes associated with lower speed limits are not necessarily sufficient in the 5 mi/h speed-limit reduction case to unambiguously influence the frequency and severity of crashes—but they are sufficient to produce unambiguous decreases in the frequency and severity of crashes 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 flashers are an effective safety countermeasure, but only clearly so if the speed-limit reduction is 10 mi/h. As a final point, it should be noted that the data used in this study only included speed-limit reductions of 5 mi/h (from 60 to 55 mi/h and from 55 to 50 mi/h) and 10 mi/h (from 65 to 55 mi/h). A fruitful area for further research would be to consider the effect of different base speed limits and speed-limit reductions.

[11] Along the lines of the discussion in footnote 7, there is the possibility that speed-limit reductions 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.

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