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Differences in rural and urban driver-injury severities in accidents involving large-trucks: An exploratory analysis

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Abstract

This study explores the differences between urban and rural driver injuries (both passenger-vehicle and large-truck driver injuries) in accidents that involve large trucks (in excess of 10,000 pounds). Using 4 years of California accident data, and considering four driver-injury severity categories (no injury, complaint of pain, visible injury, and severe/fatal injury), a multinomial logit analysis of the data was conducted. Significant differences with respect to various risk factors including driver, vehicle, environmental, road geometry and traffic characteristics were found to exist between urban and rural models. For example, in rural accidents involving tractor–trailer combinations, the probability of drivers' injuries being severe/fatal increased about 26% relative to accidents involving single-unit trucks. In urban areas, this same probability increased nearly 700%. In accidents where alcohol or drug use was identified as being the primary cause of the accident, the probability of severe/fatal injury increased roughly 250% percent in rural areas and nearly 800% in urban areas. While many of the same variables were found to be significant in both rural and urban models (although often with quite different impact), there were 13 variables that significantly influenced driver-injury severity in rural but not urban areas, and 17 variables that significantly influenced driver-injury severity in urban but not rural areas. We speculate that the significant differences between rural and urban injury severities may be at least partially attributable to the different perceptual, cognitive and response demands placed on drivers in rural versus urban areas.

Keywords: Injury severity; Truck accidents; Urban/rural differences; Multinomial logit

1. Introduction

Data maintained by the National Highway Traffic Safety Administration between 1992 and 2002 show that each year approximately 4700 persons are killed nationwide in accidents involving large-trucks. And, of these fatalities, approximately 85% are the occupants of non-truck vehicles according (Federal Motor Carrier Safety Administration, 2004). Many studies have found that large trucks are over-represented both in terms of the number of fatal accidents with passenger vehicles and in the number of fatal accidents with each other (Wolf and Carsten, 1982; Eicher et al., 1982; Campbell et al., 1988). In general terms, large trucks (defined as having a gross vehicle weight in excess of 10,000 pounds) have been found to historically account for approximately 3.5% of the total vehicle fleet, 7% of all motor vehicle travel and 12% of all traffic fatalities. And, this disproportionately high involvement in fatal accidents has been relatively constant in recent decades (Cerrelli, 1998).

Many factors, including roadway geometrics, traffic conditions, roadway and environmental conditions, driver and vehicle characteristics, are known to affect accident frequency and severity. Recent work has found that accident severities vary significantly between rural and urban locations (Lee and Mannering, 2002). The reasons for the

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observed rural/urban differences likely relate to factors such as driver behavior, characteristics of driver populations, and the effect of driver behavior as a function of the visual "noise". All of these factors can be expected to vary between rural and urban areas in ways that may not be directly observable to analysts given the limitations of current data. Thus, the distinction between elements contributing to rural and urban accident severities is potentially critical, particularly in the case of accidents involving large trucks where one would expect the interaction between driver behavior and resulting accident severity to be more pronounced.

To date, most studies that have analyzed large-truck safety have focused on accident frequency. Of the studies that have concentrated on the severity of accidents involving large-trucks, some have focused on specific injury severity types such as fatal injury (Shibata and Fukuda, 1994) thus limiting the range of information that can be extracted from their findings. Others have been limited by the use of aggregate data, resulting in a loss of information relative to disaggregate data. The intent of this study is to work with a disaggregate accident-database that will allow an in-depth analysis of the factors that determine the large-truck accident severity, measured in terms of four driver-injury categories (no injury, complaint of pain, visible injury, and severe/fatal injury). Using a multinomial discrete-probability modeling approach, our data are sufficiently detailed to allow us to untangle the complex interactions between roadway geometrics, driver characteristics, environmental factors, vehicle characteristics, and the location of the accident (rural versus urban). As will be shown, the model estimation results provide valuable insight into the nature of driver-injury severities (both passenger-vehicle and large-truck driver injuries) in accidents involving large trucks.

2. Literature review

From an engineering/human factor perspective, roadway geometrics (such as horizontal and vertical curves, lane widths, and shoulder widths), driver characteristics and behavior (such as age, use of restraints, intoxication, attentiveness and speeding), environmental factors (such as rain, fog, and snow) and vehicle characteristics (such as vehicle type and weight) can all be expected to influence to the severity of large-truck-involved accidents. While countless studies have analyzed accident severities considering all vehicle types (Evans, 1986a, 1986b; Kim et al., 1995; Laberge-Nadeau et al., 1992), there is a growing body of literature that has focused on the differential impacts of specific vehicle types. For example, Ulfarsson and Mannering (2004) consider the injury severity of multivehicle accidents that involve different passenger vehicle types (sport utility vehicles, minivans, pick-up trucks) and Chirachavala et al. (1984), Brown and Bass (1997), Shao (1987), Alassar (1988), Edwards (1998), Campbell (1991) and Chang and Mannering (1999) all look at accident severities that involve large trucks. These studies have provided a wealth of information on the determinants of accident severity when large trucks are involved including insight, to varying degrees, on how injury severities are influenced by the types of vehicles involved in the accident, driver characteristics, restraint usage, alcohol impairment, environmental factors, roadway geometrics and other related factors.

However, in reviewing past research on injury severities in accidents involving large trucks, two points are noteworthy. First, few if any large-truck accident severity studies have explicitly addressed the effect of driving environments on accident severity—specifically the difference between rural and urban environments. There is a significant and growing body of human-factors literature that indicates that there are significant differences in the demands placed on drivers in rural and urban environments. The emphasis of much of this work has been on the demands placed on drivers as a result of environmental complexities (Miura, 1990). As a recent example, Horrey and Wickens (2003) provide empirical evidence that the perceptual, cognitive and response demands placed on drivers are significantly higher in urban relative to rural areas. The effect of differences in driver demands, coupled with different traffic conditions, roadway design characteristics, and driver populations between rural and urban locations, can be expected to impact the severity of vehicular accidents. In fact, this has been shown to be the case in the recent work of Lee and Mannering (2002) in which they found that rural and urban accident locations produced very different effects on resulting injury severities.

A second point that has yet to be explored in the literature is the effect that the at-fault driver may have on accident severity. An important question to ask is whether accidents caused by large-truck drivers are more or less severe than accidents caused by passenger-vehicle drivers. Because the skill sets and attentiveness of these two types of drivers likely vary, this is a potentially important issue to explore.

3. Methodology

The measure of accident severity that we will use is the injury-level sustained by the driver given that an accident has occurred. Our database has four injury-severity categories: no injury, complaint of pain, visible injury, and severe/fatal injury. Given that four discrete outcomes are possible, an appropriate statistical modeling approach would be to use an ordered discrete probability model which will explicitly recognize the increasing severity of the four categories in the model estimation (from no injury to severe/fatal injury). These types of models have been previously applied to accident severity models by Kockelman and Kweon (2002) and Abdel-Aty (2003). However, ordered models may not always be appropriate for accident severity data because they can restrict the influence of explanatory variables on severity outcomes. For example, if an airbag is activated in a collision, we would expect a reduction in the probability of a fatality, but there may also be a reduction in the probability of “no injury” because vehicle occupants may have a complaint of pain or visible injuries resulting from airbag deployment. Ordered probability models restrict variables to either increase the highest severity category and decrease the lowest, or increase the lowest severity category and decrease the highest. The airbag example above, which would increase the likelihood of “interior” severity categories, cannot be readily handled in the model structure (see Washington et al. (2003), for a complete discussion of this point). As a result, we will follow the more common approach of using an unordered discrete outcome model.

To show the development of the model, consider the probability of an accident ending in a specific injury-severity level. Let $P_n(i)$ as the probability of accident n ending in injury-severity category i, such that

$$P_n(i) = P(\boldsymbol{\beta}_i \mathbf{X}_{\text{in}} + \varepsilon_{\text{in}} \geq \boldsymbol{\beta}_I \mathbf{X}_{\text{In}} + \varepsilon_{\text{In}}) \quad \forall I \neq i \tag{1}$$

where I is a set of all possible discrete outcomes (severity categories), $\mathbf{X}_{in}$ is a vector of measurable characteristics (geometric variables, environmental conditions, driver characteristics, etc.) that determine the injury severity for observation n, $\boldsymbol{\beta}_i$ is a vector of estimated coefficients, and ε_{in} is an error term accounting for unobserved effects influencing the injury severity of accident n.

It can be shown that if ε_{in} are assumed to be extreme value distributed (see McFadden, 1981), then a standard multinomial logit model results:

$$P_n(i) = \frac{\exp[\boldsymbol{\beta}_i \mathbf{X}_{in}]}{\sum_{\forall I} \exp(\boldsymbol{\beta}_I \mathbf{X}_{In})} \tag{2}$$

A potential limitation of the standard multinomial logit model (MNL) is the assumption that the unobserved effects associated with each severity category are independent from the effects in other categories. If this is not the case, and correlation among unobserved effects is present, the MNL will have specification error. Some past accident-severity research has found correlation among unobserved effects to be present (Shankar et al., 1996) and other research has not (Shankar and Mannering, 1996). When such correlation is present, a nested logit formulation is appropriate. We will test for the suitability of the MNL structure later in this paper.

With regard to interpretation of the model’s coefficients, the estimated coefficients are not sufficient to explore how changes in the explanatory variables affect outcome probabilities. The reason is that the marginal effect of a variable depends on all of the coefficients in the model, so the actual net effect cannot readily be determined from just the sign of any one coefficient. To resolve this problem, elasticities are calculated and used to assess the marginal effects. Elasticity measures the magnitude of the impact of specific variables on the outcome probabilities. Elasticity is computed from the partial derivative for each observation n (n subscripting omitted):

$$E_{x_{in}}^{P(i)} = \frac{\partial P(i)}{\partial x_{ki}} \frac{x_{ki}}{P(i)} \tag{3}$$

where $P(i)$ is the probability of severity outcome i and x_{ki} is the value of variable k for outcome i. Using Eqs. (2) and (3) gives:

$$E_{x_{ki}}^{P(i)} = [1 - P(i)]\,\beta_{ki} x_{ki} \tag{4}$$

where β_{ki} is the estimated coefficient associated with variable x_{ki}. Elasticity values can be roughly interpreted as the percent effect that a 1% change in x_{ki} has on the severity-outcome probability $P(i)$. If the computed elasticity value is less than one, the variable x_{ki} is said to be inelastic and a 1% change in x_{ki} will have less than a 1% change in severity outcome i’s selection probability. If the computed elasticity is greater than one, the variable x_{ki} is said to be elastic and a 1% change in x_{ki} will have more than a 1% change in outcome i’s selection probability.

It should be noted that elasticities are not applicable to indicator variables (those variables taking on values of 0 or 1 such as whether the truck-driver was at fault in the accident). In these cases, a pseudo-elasticity can be calculated as

$$E_{x_{ki}}^{P(i)} = \frac{\exp[\Delta(\boldsymbol{\beta}_i \mathbf{X}_i)] \sum_{\forall I} \exp(\beta_{kI} x_{kI})}{(\exp[\Delta(\boldsymbol{\beta}_i \mathbf{X}_i)] \sum_{\forall I_n} \exp(\beta_{kI} x_{kI}) + \sum_{\forall I \neq I_n} \exp(\beta_{kI} x_{kI}))} - 1 \tag{5}$$

where I_n is the set of alternate outcomes with x_k in the function determining the outcome, and I is the set of all possible outcomes. The pseudo-elasticity of a variable with respect to a severity category represents the average percent change in the probability of that injury category when the variable is changed from 0 to 1. So, a pseudo-elasticity of 0.25 for a variable in the no-injury severity category means that when the value of the variable in the sub-set of observations where $x_k = 0$ are changed from 0 to 1, the probabilities of a no-injury severity outcome for these observations in the sub-set is increased, on average, by 25%. See Washington et al. (2003) for further discussions on elasticities.

4. Data description

The sources of data for our study are the Traffic Accident Surveillance and Analysis System (TASAS), maintained by the California Department of Transportation (Caltrans), and the Statewide Integrated Traffic Records System maintained by the California Highway Patrol. TASAS is a dual database system containing a highway database and an accident database. The highway database contains data on over 15,209 miles of highways (10,985 miles of non-freeways and 4224 freeways), 48,000 segments, 19,000 intersections, and 14,000 ramps. Additional geometric data elements reflecting highway curvature were also manually added using the Caltrans Highway Video Log database.

Four years of accident data were prepared (1997–2000) to estimate the injury severity of drivers (both passenger-vehicle and large-truck drivers) in large truck-involved accidents (accidents which involved one or more trucks with a gross

Table 1
Data summary statistics (all accidents involving at least one large truck)

Variable	Percent of accidents	
	Rural	Urban
Resulting driver-injury severity		
None	77	87
Complaint of pain	9	8
Visible injury	10	4
Severe/fatal injury	4	1
Number of Vehicles involved in the accident		
Single vehicle	14	5
Two vehicles	67	67
Three vehicles	13	18
Four or five vehicles	4	8
Large-truck driver injuries		
Accidents caused by the truck driver	47	45
Accidents caused by another truck	8	6
Accidents caused by a passenger-vehicle driver	45	49
Passenger-vehicle driver injuries		
Accidents caused by the passenger-vehicle driver	45	37
Accidents caused by another passenger vehicle	20	18
Accidents caused by a large-truck driver	35	45
Accident-involved large-truck type (for trucks in sample)		
Single unit truck (with or without trailer)	19	19
Truck tractor without trailer	18	29
Combination (truck tractor with trailer)	63	53

vehicle weight in excess of 10,000 pounds). Three road types were considered: freeways (fully controlled access), expressways (partially controlled access), and conventional roads (uncontrolled access). Individual vehicles were used as the unit of observation. Thus, for example, an accident that involved two trucks and three passenger vehicles comprises five observations.

The combined database contains a broad range of variables including geometric data, weather conditions, road condition, pavement surface data, roadway terrain, driver-related data (such as age, gender, alcohol use), posted speed limit, etc. The database had complete data on 154,308 vehicles that were involved in large-truck accidents. To keep the sample at a manageable size for model estimation, complete accident information on 17,372 vehicles (11,072 observations for urban and 6300 observations for the rural model) was used in model estimation. The vehicles were drawn randomly and care was taken not to draw more than one vehicle from any one accident.[1]

Table 1 presents summary statistics for the data categorized by rural and urban locations. In the California databases, urban areas are defined as incorporated areas with populations of 5000 or more, with all else classified as rural. Table 1 indicates that in both rural and urban settings, two-vehicle accidents are predominant but rural areas have a higher percentage of single-vehicle large-truck accidents. For injuries to large-truck drivers, there was roughly equal chance that the accident would have been caused by the truck's driver or the driver of a passenger vehicle. For injuries to passenger-vehicle drivers involved in large-truck accidents, there is a slightly greater chance that the truck driver caused the accident in urban areas (relative to the passenger-vehicle driver) and a slightly higher chance that the passenger-vehicle driver caused the accident in rural areas (relative to the truck-driver being the cause). Finally, of the various types of large trucks, tractor–trailer combinations (which are referred to as articulated vehicles in some countries) are the most likely to be involved in both rural and urban accidents relative to single-unit trucks and tractors operating without an accompanying trailer.

5. Model estimation results

The sample data were divided into two datasets, one for accidents occurring in rural areas and the other for accidents occurring in urban areas. During model estimation, variables were included in the specification if they had *t*-statistics in excess of 1.96 (absolute value), corresponding to the 95% confidence interval on a two-tailed *t*-test.

The final rural-model specification is presented in Table 2 and the corresponding psuedo elasticities are presented in Table 3. The tables show that a wide variety of variables were found to significantly influence driver-injury severity with a total of 50 coefficients estiamted.[2] Overall model fit is quite good with a ρ^2 of 0.5207, suggesting that the model fits the data well.[3]

Turning to an assessment of some of the model's coefficients, Table 3 shows that, relative to large-truck driver injuries caused by other large-trucks and passenger-vehicle driver injuries in accidents where the injured driver did not

[1] From a modeling perspective this is desirable because having more than one vehicle from any given accident could cause a correlation of unobserved effects (shared unobservables that can be attributed to a specific accident) that would complicate the model estimation.

[2] Note that in Table 2, separate coefficients were estimated for some variables for specific outcomes. For example, for "Vehicle move preceding accident: making right/left turn", three separate coefficients were estimated. The criteria used to determine whether this separation of estimates based on outcomes was justified was to conduct a likelihood ratio test with $X^2 = -2[\mathrm{LL}(\boldsymbol{\beta}_R) - \mathrm{LL}(\boldsymbol{\beta}_U)]$ where $\mathrm{LL}(\boldsymbol{\beta}_R)$ is the model's log-likelihood at convergence when the coefficients are restricted to be one value (across possible injury outcomes) and $\mathrm{LL}(\boldsymbol{\beta}_U)$ is the model's log-likelihood at convergence when the coefficients are unrestricted (separate coefficients are estimated across outcomes). This statistic (X^2) is χ^2 distributed with degrees of freedom equal to the difference in the number of estimated restricted and unrestricted coefficients (see Washington et al., 2003). When the resulting χ^2-value gave us over 95% confidence to reject the null hypothesis that the coefficient should be restricted, we used the unrestricted coefficient estimates.

[3] The ρ^2 is a measure of overall statistical fit (similar to R^2 for simple regression models) and is computed as $1 - \mathrm{LL}(\boldsymbol{\beta})/\mathrm{LL}(\mathbf{0})$ where $\mathrm{LL}(\boldsymbol{\beta})$ is the model's log likelihood at convergence and $LL(\mathbf{0})$ is the log-likelihood when all coefficients are set to 0. This statistic is sometimes referred to as the likelihood ratio index and is a measure of the likelihood improvement attributable to estimated coefficients. See Washington et al. (2003) for additional detail and examples.

Table 2
Multinomial logit model of driver-injury severity in rural areas

Variable[a]	Estimated coefficient	t-Statistic
Constant [1]	2.307	14.09
Constant [2]	0.357	2.09
Constant [3]	0.579	5.07
Large-truck driver injury when causing the accident [1]	1.099	8.11
Large-truck driver injury when accident caused by passenger vehicle [1]	0.871	7.02
Passenger-vehicle driver injury when causing the accident [1,2]	−0.469	−4.54
Vehicle type: truck tractor without trailer [1]	−0.705	−5.01
Vehicle type: combination (truck tractor with trailer) [1]	−0.323	−2.83
Vehicle occupancy: 2 [1]	−0.602	−7.47
Vehicle occupancy: 4 or 5 [1]	−0.516	−3.33
Male driver [1]	0.488	4.68
Male driver [2]	−0.495	−3.91
Vehicle violation: excessive speed [3]	0.532	3.22
Vehicle move preceding accident: stopped in roadway [1,2]	2.064	7.54
Vehicle move preceding accident: proceeding straight [1,2]	0.693	7.43
Vehicle move preceding accident: make right/left turn [1]	2.222	4.72
Vehicle move preceding accident: make right/left turn [2]	1.663	3.32
Vehicle move preceding accident: make right/left turn [3]	1.257	2.57
Vehicle move preceding accident: slowing or stopping [1,2]	1.639	6.67
Vehicle move preceding accident: changing lane [1]	1.009	5.46
Object struck [1]	0.520	3.97
First location of collision: interior lanes [1]	0.533	3.07
Second location of collision: beyond left shoulder [1]	−1.295	−8.94
Second location of collision: left lane [1]	−1.497	−5.88
Second location of collision: left lane [2]	−1.110	−3.45
Second location of collision: left lane [3]	−0.905	−2.95
Second location of collision: beyond right shoulder [1]	−1.385	−11.15
Associated factor with collision: stop and go traffic [3]	−2.771	−2.75
Single-vehicle accident (truck) [2,3]	0.943	6.72
Two-vehicle accidents [1]	0.284	3.34
Highway location: intersection area [1]	−0.741	−6.09
Number of directional lanes: 2 or 3 [1]	−0.477	−5.75
Number of directional lanes: 4 or 5 [3]	0.262	2.44
Number of directional lanes: 6 or 7 [3]	0.533	2.83
Highway terrain is rolling [3]	−0.246	−2.39
Concrete median barrier (with and without glare screen) [4]	−1.193	−2.83
Roadway design speed: 65 mph [2]	−0.300	−2.64
Road lighting: dusk-dawn [1]	−0.704	−4.04
Road lighting: dark no street light [1]	−0.352	−3.99
Collision type: rear end [2,3]	0.604	7.22
Collision type: other types [1]	1.056	6.90
Primary collision factor: driving under the influence (alcohol or drug) [1]	−1.443	−6.42
Primary collision factor: driving under the influence (alcohol or drug) [2]	−0.999	−3.37
Primary collision factor: driving under the influence (alcohol or drug) [3]	−0.756	−3.06
Primary collision factor: improper passing [1]	0.725	3.02
Vehicle model year 1981–1988 inclusive [1]	−0.241	−3.02
Foreign made vehicle [2,3]	0.371	4.13
Travel time (morning rush hour between 5:31 and 8:00 a.m.) [2]	0.419	3.08
Travel time (off-peak traffic between 8:01 a.m. and 3:00 p.m.) [2]	0.280	2.68
Collision year: 1998 [3]	−0.262	−2.49
Log likelihood at zero [LL($\mathbf{0}$)]	−8733.7	
Log likelihood at convergence [LL($\boldsymbol{\beta}$)]	−4185.4	
Number of observations used	6300	
ρ^2	0.52	

[a] Numbers in parentheses indicates variables defined for: [1] no injury, [2] complaint of pain, [3] visible injury. The severe/fatal injury outcome has, without loss of generality, its coefficients normalized to zero.

Table 3
Average pseudo-elasticities of driver-injury severity in rural areas

Variable	Pseudo-elasticities[a]			
	[1]	[2]	[3]	[4]
Large-truck driver injury when causing the accident	0.226	−0.592	−0.592	−0.592
Large-truck driver injury when accident caused by passenger vehicle	0.198	−0.499	−0.499	−0.499
Passenger-vehicle driver injury when causing the accident	−0.058	−0.058	0.505	0.505
Vehicle type: truck tractor without trailer	−0.174	0.671	0.671	0.671
Vehicle type: combination (truck tractor with trailer)	−0.090	0.257	0.257	0.257
Vehicle occupancy: 2	−0.136	0.577	0.577	0.577
Vehicle occupancy: 4 or 5	−0.124	0.469	0.469	0.469
Male driver	0.240	−0.536	−0.239	−0.239
Vehicle violation: excessive speed	−0.058	−0.058	0.603	−0.058
Vehicle move preceding accident: stopped in roadway	0.166	0.166	−0.852	−0.852
Vehicle move preceding accident: proceeding straight	0.090	0.090	−0.455	−0.455
Vehicle move preceding accident: make right/left turn	0.182	−0.324	−0.549	−0.872
Vehicle move preceding accident: slowing or stopping	0.146	0.146	−0.777	−0.777
Vehicle move preceding accident: changing lane	0.200	−0.562	−0.562	−0.562
Object struck	0.108	−0.341	−0.341	−0.341
First location of collision: interior lanes	0.115	−0.345	−0.345	−0.345
Second location of collision: beyond left shoulder	−0.323	1.472	1.472	1.472
Second location of collision: left lane	−0.176	0.213	0.490	2.681
Second location of collision: beyond right shoulder	−0.341	1.631	1.631	1.631
Associated factor with collision: stop and go traffic	0.116	0.116	−0.930	0.116
Single vehicle accident (single vehicle is truck)	−0.201	1.054	1.054	−0.201
Multi-vehicle accident (two-vehicles involved)	0.077	−0.189	−0.189	−0.189
Highway location: intersection area	−0.177	0.725	0.725	0.725
Number of directional lanes: 2 or 3	−0.101	0.448	0.448	0.448
Number of directional lanes: 4 or 5	−0.028	−0.028	0.263	−0.028
Number of directional lanes: 6 or 7	−0.061	−0.061	0.600	−0.061
Highway terrain is rolling	0.024	0.024	−0.199	0.024
Concrete median barrier (with and without glare screen)	0.031	0.031	0.031	−0.687
Roadway design speed: 65 mph	0.026	−0.240	0.026	0.026
Road lighting: dusk-dawn	−0.172	0.675	0.675	0.675
Road lighting: dark no street light	−0.081	0.307	0.307	0.307
Collision type: rear end	−0.118	0.612	0.612	−0.118
Collision type: other types	0.218	−0.576	−0.576	−0.576
Primary collision factor: driving under the influence (alcohol or drug)	−0.183	0.274	0.625	2.460
Primary collision factor: improper passing	0.149	−0.444	−0.444	−0.444
Vehicle model year between 1981 and 1988 (inclusive)	−0.054	0.204	0.204	0.204
Foreign-made vehicle	−0.068	0.350	0.350	−0.068
Travel time (morning rush hour between 5:31 and 8:00 a.m.)	−0.043	0.455	−0.043	−0.043
Travel time (off-peak traffic between 8:01 a.m. and 3:00 p.m.)	−0.028	0.286	−0.028	−0.028
Collision year: 1998	0.025	0.025	−0.211	0.025

[a] Numbers in parentheses indicates variables defined for: [1] no injury, [2] complaint of pain, [3] visible injury, [4] severe/fatal injury outcomes. As an example for interpreting pseudo-elasticities, value of 0.25 for a variable in a specific outcome (say complaint of pain) means that when the value of the variable in a sub-set of observations where values of 0 are changed from 0 to 1, the probability of a complaint of pain injury for this sub-set of observations is increased, on average, by 25%.

cause the accident (accidents caused by a truck driver or another passenger-vehicle driver), the probability of a large-truck-driver not being injured (or complaining of pain) is 22.6% higher when the accident is caused by the truck driver and 19.8% higher when the accident is caused by the passenger-vehicle driver.[4] This reflects the lower severity of truck-driver injury when causing the accident or having the accident caused by a passenger vehicle. Interestingly, on average, there was a 50.5% increase in the likelihood of visible injury and severe/fatal injury for passenger-vehicle drivers when the accident was caused by the injured driver, relative to large-truck driver injuries caused by other large-trucks and passenger-vehicle driver injuries in accidents where the injured driver did not cause the accident (see Table 3). In rural areas, this is an important finding on the effect of causality on injury severity.

With regard to the type of large trucks involved in the accident (see Table 1 for sample percentages), relative to

[4] Note that the elasticities presented in Table 3 (and later Table 5) are dependent on all of the variables in the model (Tables 2 and 4), including those defined for all alternative outcomes, as indicated in Eq. (5). Also, note that each accident generates an elasticity and the values presented in Tables 3 and 5 are the average values over all of these accidents.

accidents involving single-unit large trucks, accidents involving tractor-trailer combinations had a 9% decrease in no injury and a 25.7% increase in complaint of pain, visible injury and severe/fatal injury probabilities across drivers. For truck tractors without trailers, there was a 17.4% decrease in the probability of no injury and a 67.1% increase in complaint of pain, visible injury and severe/fatal injury probabilities across drivers. These findings show that, as might be expected, multiple-unit trucks and large tractors tend to increase accident severities relative to single-unit large trucks.

When driving under the influence of alcohol or drugs was identified as the primary collision factors (this was the case in 4% of all rural accidents in the database), the differential effects on all driver-injury severity categories were significant. Relative to accidents where alcohol and drug use was not a primary cause, the probability of no injury to the driver decreased 18.3%, the probability of complaint of pain increased 27.4%, the probability of visible injury increased 62.5% and the probability of severe/fatal injury increased 246%. These sobering findings corroborate national aggregate data that also show the devastating effect of alcohol and drugs on injury severities.

The final urban-model specification is presented in Table 4 and the corresponding psuedo elasticities are presented in Table 5. As with the rural model, a wide variety of variables were found to significantly influence driver-injury severity (55 estimated coefficients) with good overall model fit (ρ^2 of 0.69).

Turning to an assessment of some of the model's coefficients, Table 5 shows that drivers that caused the accident had a very strong influence on injury outcomes. For example, relative to passenger-vehicle injuries in accidents caused by other passenger vehicles, large-truck driver injuries when large-truck drivers caused the accident had probabilities that were 62% lower for complaint of pain, 34.5% lower for visible injury, and 96.4% lower for severe/fatal injury. And, when passenger-vehicle drivers caused the accident they had a 107.5% increase in the probability of visible injury and severe/fatal injury relative to the case where the passenger-vehicle driver injury was caused by another passenger vehicle. These factors underscore the important and complex effect that driver accident causality has on injury severity and the difference between these effects in urban and rural locations.

Relative to accidents involving single-unit large trucks, accidents involving tractor–trailer combinations had a 3.1% decrease in no injury, a 33.4% decrease in complaint of pain, an 11.1% decrease in visible injury and a 689.3% increase on severe/fatal injury probabilities across drivers. For truck tractors without trailers, there was a 7.7% decrease in no injury, complaint of pain, and visible injury probabilities and 951.8% increase in severe/fatal injury probabilities across drivers. These findings are substantially different than the rural findings (see Table 6) and underscore the major role that multiple-unit trucks and large tractors play in determining urban accident severities relative to single-unit large trucks.

As was the case with rural areas, in urban areas when driving under the influence of alcohol or drugs was identified as the primary collision factors (which was the case in 2% of all accidents in the database), the differential effects on driver-injury severity categories were significant. Relative to accidents where alcohol and drug use was not the primary cause, the probability of no injury to the driver and complaint of pain both decreased 12.9%, the probability of visible injury increased 204.7% and the probability of severe/fatal injury increased 798%. These findings show that the adverse effect of alcohol and drug involvement on injury severities in urban areas is even more pronounced than in rural areas (see Table 7 for a summary of drug and alcohol impacts).

Aside from the highlighted comparisons between urban and rural models presented above, there are many other differences between the two models.[5] This becomes apparent when one considers the number of variables found to be significant in the rural model but not in the urban model and the number of variables found to be significant in the urban model but not in the rural model. These variables are listed in Table 8 along with the effect that they have on overall injury severity. This table further underscores the significant difference between urban and rural large-truck accident severities.

6. Model specification tests

Several model specification issues were examined to ensure that the models previously presented were statistically sound. One specification issue relates to our use of a simple multinomial logit model structure as opposed to possible nested logit model structures. This is potentially important because various injury categories could share unobserved effects that would violate the multinomial logit assumption of independence of unobserved effects across discrete outcome categories. For example, one might speculate that no injury and complaint of pain categories may share unobserved effects that are associated with minor accidents and that evident injury and severe/fatal injury might share unobserved effects associated with serious accidents. If this is the case, the use of a simple multinomial logit model structure will be invalid and a nested logit structure should be used. As previously mentioned, the injury-severity literature on this topic is mixed with some researchers finding simple multinomial logit structures to be valid (Shankar and Mannering, 1996) and others finding nested logit structures to be appropriate (Shankar et al., 1996).

To test alternate model structures, four alternate nested logit structures were estimated for both urban and rural mod-

[5] Likelihood ratio tests indicate that the null hypothesis that urban and rural models are the same can be rejected with well over 99% confidence. Examples of such likelihood ratio tests are shown later in this paper.

Table 4
Multinomial logit model of driver-injury severity in urban areas

Variable[a]	Estimated coefficient	*t*-Statistic
Constant [1]	3.546	16.08
Constant [2]	2.302	11.87
Constant [3]	1.418	8.66
Large-truck driver injury when causing the accident [1]	3.431	4.96
Large-truck driver injury when causing the accident [2]	2.353	3.34
Large-truck driver injury when causing the accident [3]	2.898	4.11
Large-truck driver injury when accident caused by another truck [4]	−3.225	−2.78
Large-truck driver injury when accident caused by passenger vehicle [1]	2.501	3.99
Large-truck driver injury when accident caused by passenger vehicle [2]	1.988	3.11
Large-truck driver injury when accident caused by passenger vehicle [3]	1.848	2.85
Passenger-vehicle driver injury when causing the accident [1,2]	−0.773	−6.74
Passenger-vehicle driver injury in accident caused by truck [2]	0.334	3.78
Vehicle type: truck tractor without trailer [4]	2.433	3.78
Vehicle type: combination (truck tractor with trailer) [1]	−2.098	−3.47
Vehicle type: combination (truck tractor with trailer) [2]	−2.472	−4.00
Vehicle type: combination (truck tractor with trailer) [3]	−2.183	−3.50
Vehicle occupancy: 2 [1]	−0.499	−6.61
Male driver [1]	0.253	2.35
Male driver [2]	−0.478	−3.86
Driver age between 15 and 22 [3]	0.367	2.52
Vehicle move preceding accident: stopped in roadway [1]	0.550	4.33
Vehicle move preceding accident: proceeding straight [1,3]	0.576	5.80
Vehicle move preceding accident: make right/left turn [1]	1.405	6.23
Vehicle move preceding accident: slowing or stopping [1]	0.349	2.61
Vehicle move preceding accident: changing lane [1]	0.738	6.00
Vehicle move preceding accident: merging [1]	1.212	5.04
Object struck [4]	1.332	4.09
First location of collision: beyond left shoulder [2,3]	1.275	7.78
First location of collision: left lane [1]	−0.238	−2.38
Second location of collision: beyond left shoulder [1]	−0.926	−6.58
Second location of collision: interior lanes [1]	−0.232	−2.44
Second location of collision: beyond right shoulder [1]	−1.955	−12.61
Second location of collision: beyond right shoulder [2]	−0.474	−2.51
Associated factor: stop and go traffic [1]	0.380	3.12
Multi-vehicle accident (2 vehicles involved) [1]	0.939	11.05
Multi-vehicle accident (3 vehicles involved) [1]	0.385	4.26
Accident occurred in a on/off ramp area [4]	−1.551	−2.62
Highway location: intersection area [2]	0.943	4.33
Highway type: conventional road (unrestricted access) [1]	−0.338	−3.02
Inside city limit [1,2]	0.422	3.84
Three beam median barrier (with and without glare screen) [1,2]	0.558	2.82
Median type: unpaved median [1]	−0.331	−4.86
Road condition: construction zone [2]	0.356	2.53
Weather: raining [2]	0.420	3.02
Collision type: rear end [1]	−0.678	−7.91
Collision type: rear end [3]	−0.465	−3.82
Collision type: broadside [1]	−0.930	−7.44
Collision type: other types [1]	0.682	3.71
Primary collision factor: driving under the influence (alcohol or drug) [1,2]	−2.333	−8.49
Primary collision factor: driving under the influence (alcohol or drug) [3]	−1.081	−3.51
Primary collision factor: improper passing [1]	0.949	2.43
Vehicle model older than 1981 [1,2]	−0.652	−4.21
Foreign made vehicle [1]	−0.193	−2.79
Travel time (morning rush hour between 5:31 and 8:00 a.m.) [1,2]	0.486	3.17
Travel time (afternoon rush hour between 3:01 and 6:30 p.m.) [1,2]	0.483	3.74
Primary collision factor: improper passing [1]	0.949	2.43
Vehicle model older than 1981 [1,2]	−0.652	−4.21
Foreign made vehicle [1]	−0.193	−2.79
Travel time (morning rush hour between 5:31 and 8:00 a.m.) [1,2]	0.486	3.17
Travel time (afternoon rush hour between 3:01 and 6:30 p.m.) [1,2]	0.483	3.74

Table 4 (*Continued*)

Variable[a]	Estimated coefficient	*t*-Statistic
Log likelihood at zero [LL(**0**)]	−15349	
Log likelihood at convergence [LL(**β**)]	−4788	
Number of observations	11072	
ρ^2	0.69	

[a] Numbers in parentheses indicates variables defined for: [1] no injury, [2] complaint of pain, [3] visible injury. The severe/fatal injury outcome has, without loss of generality, its coefficients normalized to zero.

Table 5
Average pseudo-elasticities of driver-injury severity (urban area)

Variable	Pseudo-elasticities[a]			
	[1]	[2]	[3]	[4]
Large-truck driver injury when causing the accident	0.117	−0.620	−0.345	−0.964
Large-truck driver injury when accident caused by another truck	0.010	0.010	0.010	−0.960
Large-truck driver injury when accident caused by passenger vehicle	0.086	−0.350	−0.435	−0.911
Passenger-vehicle driver injury when causing the accident	−0.043	−0.043	1.073	1.073
Passenger-vehicle driver injury in accident caused by truck	−0.023	0.364	−0.023	−0.023
Vehicle type: truck tractor without trailer	−0.077	−0.077	−0.077	9.518
Vehicle type: combination (truck tractor with trailer)	−0.031	−0.334	−0.111	6.893
Vehicle occupancy: 2	−0.069	0.533	0.533	0.533
Male driver	0.117	−0.462	−0.132	−0.132
Driver age between 15 and 22	−0.017	−0.017	0.420	−0.017
Vehicle move preceding accident: stopped in roadway	0.063	−0.386	−0.386	−0.386
Vehicle move preceding accident: proceeding straight	0.049	−0.410	0.049	−0.410
Vehicle move preceding accident: make right/left turn	0.136	−0.721	−0.721	−0.721
Vehicle move preceding accident: slowing or stopping	0.042	−0.265	−0.265	−0.265
Vehicle move preceding accident: changing lane	0.089	−0.479	−0.479	−0.479
Vehicle move preceding accident: merging	0.124	−0.666	−0.666	−0.666
Object struck	−0.022	−0.022	−0.022	2.708
First location of collision: beyond left shoulder	−0.207	1.837	1.837	−0.207
First location of collision: left lane	−0.033	0.226	0.226	0.226
Second location of collision: beyond left shoulder	−0.148	1.150	1.150	1.150
Second location of collision: interior lanes	−0.031	0.222	0.222	0.222
Second location of collision: beyond right shoulder	−0.299	2.082	3.951	3.951
Associated factor: stop and go traffic	0.049	−0.283	−0.283	−0.283
Multi-vehicle accident (two vehicles involved)	0.157	−0.548	−0.548	−0.548
Multi-vehicle accident (three vehicles involved)	0.044	−0.290	−0.290	−0.290
Accident occurred in a on/off ramp area	0.009	0.009	0.009	−0.786
Highway location: intersection area	−0.103	1.303	−0.103	−0.103
Highway type: conventional road (unrestricted access)	−0.048	0.334	0.334	0.334
Inside city limit	0.026	0.026	−0.327	−0.327
Three beam median barrier (with and without glare screen)	0.024	0.024	−0.414	−0.414
Median type: unpaved median	−0.045	0.329	0.329	0.329
Road condition: construction zone	−0.033	0.381	−0.033	−0.033
Weather: raining	−0.039	0.463	−0.039	−0.039
Collision type: rear end	−0.070	0.831	0.150	0.831
Collision type: broadside	−0.148	1.159	1.159	1.159
Collision type: other types	0.081	−0.453	−0.453	−0.453
Primary collision factor: driving under the influence (alcohol or drug)	−0.129	−0.129	2.047	7.979
Primary collision factor: improper passing	0.103	−0.573	−0.573	−0.573
Vehicle model older than 1981	−0.041	−0.041	0.840	0.840
Foreign made vehicle	−0.022	0.186	0.186	0.186
Travel time (morning rush hour between 5:31 and 8:00 a.m.)	0.022	0.022	−0.371	−0.371
Travel time (afternoon rush hour between 3:01 and 6:30 p.m.)	0.023	0.023	−0.369	−0.369

[a] Numbers in parentheses indicates variables defined for: [1] no injury, [2] complaint of pain, [3] visible injury, [4] severe/fatal injury outcomes. As an example for interpreting pseudo-elasticities, value of 0.25 for a variable in a specific outcome (say complaint of pain) means that when the value of the variable in a sub-set of observations where values of 0 are changed from 0 to 1, the probability of a complaint of pain injury for this sub-set of observations is increased, on average, by 25%.

Table 6
The impact on injury severity as a function of the type of large truck involved in the accident

Variable	Percent change in injury probabilities[a]	
	Rural	Urban
Resulting driver-injury severity when large truck is a truck tractor without trailer		
None	−17.4	−7.7
Complaint of pain	67.1	−7.7
Visible injury	67.1	−7.7
Severe/fatal injury	67.1	951.8
Resulting driver-injury severity when large truck is a combination (truck tractor with trailer)		
None	−9.0	−3.1
Complaint of pain	25.7	−33.4
Visible injury	25.7	−11.1
Severe/fatal injury	25.7	689.3

[a] Percent change relative to large-truck accidents involving single-unit trucks.

Table 7
The impact on injury severity when driving under the influence of alcohol and drugs is identified as the primary cause of the accident

Variable	Percent change in injury probabilities[a]	
	Rural	Urban
None	−18.3	−12.9
Complaint of pain	27.4	−12.9
Visible injury	62.5	204.7
Severe/fatal injury	246.0	797.9

[a] Percent change relative to when alcohol and drugs are not identified as the primary cause of accidents.

els. The first had no-injury as an outcome alone and had all other injury categories included in a single nest (the assumption being that complaint of pain, visible injury and severe/fatal injury shared unobserved effects). The second had no-injury and complaint of pain in a nest (the assumption being that these low-injury outcomes shared unobserved effects) and visible injury and severe injury as outcomes alone. The third model structure had no injury and complaint of pain outcomes alone with visible injury and severe/fatal injury in a nest (the assumption being that these two injury outcomes shared unobserved effects). Finally, the fourth model structure had no-injury and complaint of pain in one nest and visible injury and severe/fatal injury in the other nest. In all of these model structures, for both rural and urban data, the

Table 8
Notable specific estimation results that were observed generally across models, showing similarities and differences between urban/rural, both in direction and size of effects of variables on severity probabilities

Variable	Effect on injury severity
Variables significant in rural but not urban	
Vehicle occupancy: 4 or 5	Increases (decreases no injury)
Vehicle violation: excessive speed	Increases (increases visible injury)
First location of collision: interior lanes	Decreases (increases no injury)
Second location of collision: left lane	Increases (decreases no injury)
Single vehicle accident (single vehicle is truck)	Increases (decreases no injury)
Number of directional lanes: 2 or 3	Increases (decreases no injury)
Number of directional lanes: 4 or 5	Increases (increases visible injury)
Number of directional lanes: 6 or 7	Increases (increases visible injury)
Highway terrain is rolling	Mixed (decreases visible injury)
Concrete median barrier (with and without glare screen)	Decreases (decreases severe/fatal injury)
Vehicle model year between 1981 and 1988 (inclusive)	Increases (decreases no injury)
Travel time (off-peak traffic between 8:01 a.m. and 3:00 p.m.)	Mixed (increases complaint of pain)
Collision year: 1998	Mixed (decreases visible injury)
Variables significant in urban but not rural	
Large-truck driver injury when accident caused by another truck	Decreases (decreases severe/fatal injury)
Passenger-vehicle driver injury in accident caused by truck	Mixed (increases complaint of pain)
Driver age between 15 and 22	Increases (increases visible injury)
Vehicle move preceding accident: merging	Decreases (increases no injury)
First location of collision: beyond left shoulder	Increases (decreases no injury)
First location of collision: left lane	Increases (increases complaint of pain and visible injury)
Second location of collision: interior lanes	Increases (decreases no injury)
Accident occurred in a on/off ramp area	Decreases (decreases severe/fatal injury)
Highway type: conventional road (unrestricted access)	Increases (decreases no injury)
Inside city limit	Decreases (increases no injury and complaint of pain)
Three beam median barrier (with and without glare screen)	Decreases (increases no injury and complaint of pain)
Median type: unpaved median	Increases (decreases no injury)
Road condition: construction zone	Mixed (increases complaint of pain)
Weather: raining	Mixed (increases complaint of pain)
Collision type: broadside	Increases (decreases no injury)
Vehicle model year older than 1981	Increases (increases visible injury and severe fatal injury)
Travel time (afternoon rush hour between 3:01 and 6:30 p.m.)	Mixed (increases complaint of pain)

validity of the simple multinomial logit model could not be rejected with any reasonable level of confidence.[6]

Another specification issue we addressed was to test whether our coefficient estimates were stable (i.e., produced estimates that were not significantly different) across sub-sets of our data. To test the stability of the estimated rural model coefficients, the data used to estimate the rural injury-severity model was randomly divided into two roughly equal sub-samples. Using the same variables as in the full-data model (as shown in Table 2), two additional models were estimated (one for each sub-sample of data). The appropriate test to determine whether the coefficient estimates are stable over the sub-sets of data is the likelihood-ratio test:

$$X^2 = -2[\mathrm{LL}(\boldsymbol{\beta}_\mathrm{A}^\mathrm{T}) - \mathrm{LL}(\boldsymbol{\beta}_\mathrm{A}^\mathrm{A})]$$

where $\mathrm{LL}(\boldsymbol{\beta}_\mathrm{A}^\mathrm{T})$ is the log-likelihood of sub-sample A's model using the estimated coefficients from the total-data model (as shown in Table 2) and $\mathrm{LL}(\boldsymbol{\beta}_\mathrm{A}^\mathrm{A})$ is the log-likelihood of sub-sample A's model using the converged coefficient estimates that best fit that sample. This statistic is χ^2 distributed with degrees of freedom equal to the number of coefficients in the total-data model (see Washington et al., 2003). Note that if the total data and sub-sample data produced identical coefficients, $\mathrm{LL}(\boldsymbol{\beta}_\mathrm{A}^\mathrm{T})$ would be equal to $\mathrm{LL}(\boldsymbol{\beta}_\mathrm{A}^\mathrm{A})$, indicating perfect agreement between the total data estimates and the sub-sample estimates (and producing a X^2 value of 0). With 50 degrees of freedom, the X^2 values for the two randomly drawn sub-samples were 33.4 and 34.0, indicating that the null hypothesis that the coefficients are the same cannot be rejected at reasonable confidence levels (we could reject the null hypothesis with less than 5% confidence). Similarly, randomly splitting the urban data into two sub-samples gave X^2 values of 29.2 and 26 (with 55 degrees of freedom). Again, the null hypothesis that the coefficients are the same cannot be rejected at reasonable confidence levels. Based on these experiments we can conclude that the model is reasonably stable across the data.

7. Summary and conclusions

Accident statistics show that large trucks present a serious safety problem, particularly with regard to the severity of accidents in which they are involved. In this paper, we shed additional light on large-truck accident involvement by using a large database from California to study the effect that large trucks have on driver-injury severities. Using a multinomial logit approach, a series of models are estimated to identify factors that significantly impact driver-severity outcomes (no injury, complaint of pain, visible injury, and severe/fatal injury).

Among the many interesting findings, the striking differences between the factors that determine driver-injury severity (both passenger-vehicle and large-truck driver injuries) in rural areas, and those that determine driver-injury severity in urban areas, is noteworthy. For variables that were found to be significant in both urban and rural models, the magnitudes of their impact on driver severity outcomes often varied substantially. There are many instances of this. For example, accidents involving trucks that occur at an intersection in a rural area result in a 725% increase in the likelihood of severe/fatal injury (compared to all other highway locations) whereas such accidents in urban areas actually result in a 10.3% decrease in the likelihood of a severe/fatal injury. In urban areas, accidents occurring in the morning (5:31–8:00 a.m.) are 37.1% less likely to result in a severe/fatal injury (relative to other time periods) versus a mere 4.3% lower probability of a severe/fatal injury in the same time period in rural areas. The results show that the single most influential variable in both rural and urban driver-injury severity models is when driving under the influence of alcohol or drug is identified as the primary collision factor. When this is the case, the severe/fatal injury is nearly eight times more likely to occur in an urban area and about 2.5 times more likely in a rural area relative to the cases when alcohol and drug use is not identified as the primary collision factor.

Other variables were found to be significant in either the rural or the urban model, but not both. Key among these, in terms of their impact on severity, were the presence of concrete median barriers in rural areas, which reduced the likelihood of severe/fatal injury by 68.7% and if the second location of the collision is in the left lane, which increased the likelihood of a severe/fatal injury by 268.1% in rural areas. These two findings underscore issues relating to exposure to oncoming traffic in rural areas. In urban areas, being involved in a broadside collision was found to increase the probability of a severe/fatal injury by 115.9% and pre-1981 model-year cars were associated with an 84.0% increase in the likelihood of a severe/fatal injury. This latter finding may be due to recent advances in automobile design and safety features whereas the former underscores the significance of side-impact collisions in urban settings.

The significant differences between urban and rural locations, even when many factors that distinguish these locations are explicitly accounted for in the model specification (geometrics, weather, vehicle types, driver actions, driver characteristics, etc.), suggest that complex interactions between driver behavior and measurable factors such as geometrics, environmental conditions, etc., are playing a significant role in driver-injury severity. While we can speculate that this may

[6] When estimating a nested logit structure, a log-sum coefficient is estimated. It is the coefficient associated with the natural log of the denominator of the model of the outcomes present in a nest (see the denominator of Eq. (2)). If this coefficient is equal to one, the nested model reduces to a simple multinomial model. In all of our models, this estimated coefficient(s) was not statistically different from 1, and thus the null hypothesis that the model is a simple multinomial model (and not a nested model) cannot be rejected. Alternatively, one could check directly for possible violations of the multinomial logit model's independence of irrelevant alternatives (IIAs) assumption using a test such as that developed by Small and Hsiao (1985). Our final estimated models also indicated that the multinomial logit model structure could not be statistically rejected using this test.

be a result of the different perceptual, cognitive and response demands placed on drivers, it is clear that additional research is needed to quantify these effects. Continued work with other databases, driving simulators, and future technologies that may enable researchers to download pre- and during-crash vehicle response, will begin to help us better understand rural/urban severity differences and enable the development of more effective accident-severity countermeasures.

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