Use of Heteroscedastic Ordered Logit Model to Study Severity of Occupant Injury

Distinguishing Effects of Vehicle Weight and Type

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A heteroscedastic ordered logit model was used to study the effects of various vehicle, environmental, roadway, and occupant characteristics on the severity of injuries sustained by vehicle occupants, conditional on the crash occurrence. As expected, the models found that heavier vehicles increased both a vehicle's crashworthiness and driver aggressiveness toward others. The models also found that if all passenger vehicles were to become 1,000 lb heavier, crash injury outcomes would not change dramatically. However, if all passenger cars were to become light-duty trucks (i.e., minivans, pickups, and sport utility vehicles) of the same weight, incapacitating injuries and fatalities were predicted to rise by 26% and 64%, respectively. Beyond weight and vehicle type, many other factors were controlled for as well. For example, older occupants and female occupants were more likely to experience injury and death, particularly when navigating curved roadway sections with higher speed limits.

Since 1997, the number of injuries caused by motor vehicle crashes has declined each year in the United States. However, during the same period, the number of fatalities has increased. In 2003, 43,220 deaths were reported on United States highways, the greatest number since 1990 (*1*). Some researchers attribute this change in injury severity to the revocation of the national speed limit in 1996 (*2*). Others suggest that the rise in use in recent years of sport utility vehicles (SUVs) and pickups, which are heavier than passenger cars, may be the source of the increased fatalities, as cited by the *New York Times* (*3*). Of course, most automotive manufacturers hold the view (at least publicly) that heavier vehicles are safer (*3*); this opinion is supported by several studies (*4–6*).

To untangle the contributions of vehicle type and vehicle weight, this paper examines crash consequences conditioned on crash occurrence (i.e., examines crashworthiness and aggressiveness, rather than crash frequency) while controlling for a variety of variables, including speed limits, weather, roadway design, and vehicle and occupant characteristics. By using data from the National Automotive Sampling System's crashworthiness data system (NASS CDS), both a standard and a heteroscedastic ordered logit model are calibrated.

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PREVIOUS RESEARCH

Motivated by different purposes and relying on different data sets, researchers have applied a variety of methods to analyze the influential factors in crash severity. Some experimentally tested vehicles and their restraint systems (*7, 8*), which is a costly process and one that allows for relatively few variations in control variables. Most studies rely on some type of statistical analysis of police-reported crash data. Some of these approaches are rather unsophisticated, correlating just a few variables at a time. For example, Huelke and Compton simply compared the number of unrestrained occupants with the number of belted occupants on each injury level to illustrate the effect of seat belt use (*9*). Shinohara et al. used a chi-squared test to compared injury severities between belted and unbelted occupants, compact cars and medium-size cars, and drivers and passengers (*10*).

More sophisticated approaches use multivariate analyses and discrete-response models for level of injury severity. The logistic model is a popular choice. For example, Krull et al. used a logistic model to study how driver condition, vehicle type, roadway geometrics, annual average daily traffic (AADT), speed limit, and rollover involvement affect the probability of fatal and incapacitating injuries (*11*). Bedard et al. used it to analyze how driver, crash, and vehicle characteristics contribute to driver fatalities (*5*). Toy and Hammitt modeled the risk of serious injury and death as a function of vehicle type, driver age and gender, restraint use, and configuration of the crash in two-vehicle crashes (*12*). As an extension to this approach, Dissanayake and Lu used the sequential binary logit model to find how crash and injury severity are influenced in crashes between passenger cars and fixed roadside object (*13*).

Although multinomial logit (MNL) and probit (MNP) models do not recognize order in injury levels (such as fatal crashes being worse than property-damage-only crashes) and do require far more coefficient estimates when variables are not generic (i.e., when variables do not vary by outcome type, as is the case with design, weather, vehicle, and occupant characteristics), they do avoid certain restrictions posed by standard ordered models. They allow variables to have opposing effects regardless of injury order; for example, air bags may cause more injuries but fewer fatalities (*14*). Thus, MNL and MNP models may still have a place in crash severity analysis. For example, Ulfarsson and Mannering used an MNL to study the effect of gender on injury severity across different vehicle types (*15*). Yet the most frequently used model for such analyses is an ordered logit (OL) or ordered probit (OP) model. Of these two models, the OL tends to converge more quickly (*16*), whereas the OP has a simpler statistical form and is much more common in past studies. For example, Khattak used OP models to analyze the effect of adverse weather conditions, vehicle and information technology, and driver age on injury severity (*17, 18*). Renski et al. used it to study the effect of speed limits (*2*). Kockelman and Kweon controlled for a wide variety of factors to deduce the effect of vehicle type (*19*). Their later work combined crash exposure, frequency, and severity models for a rather comprehensive risk analysis of various driver and vehicle types (*20*). Abdel-Aty calibrated different OP models for injury severity, along roadway sections, at signalized intersections, and at toll plazas (*21*). Khattak and Rocha focused on SUVs (*22*).

Extensions to the OP and OL model specifications include the ordered mixed logit model (OML), the heteroscedastic ordered probit (HOP) model, and the heteroscedastic ordered logit (HOL) model. Several crash-severity investigations have relied on these. The OML model allows for random coefficients across observational units, and the HOP and HOL models allow the error term's variance to vary. Srinivasan's OML model accommodated variable, random, and correlated injury severity thresholds (*23*). He used chi-squared tests to show that the OML model was statistically superior to the OL model. O'Donnell and Connor's work is most closely related to the models examined here (*24*). They applied HOP and HOL models to discern how injury severity is affected by occupant age; seating position; use of a seat belt; blood alcohol level; vehicle speed, type, and make; and collision type. The variance in their error terms was parameterized to be a function of occupant age, vehicle speed, vehicle year, and time of accident. They found that higher speeds and occupant age result in higher injury severity, along with head-on crashes, travel in light-duty trucks, vehicle age, being female, having a blood alcohol level >0.08%, and not wearing a seat belt. Among all these factors, they estimated seat position to have the most significant effect, with the driver's position being safest, a result that is inconsistent with most other research (*9, 25*). Their models' variance terms were minimized for 30-year-old occupants and crash times of 1:00 p.m., and they increased with travel speed.

Previous research involving vehicle type is extensive; in comparison, research distinguishing vehicle weight from vehicle type is limited. Evans and Wasielewski studied the effect of vehicle weight on serious and fatal driver injury rates in head-on crashes (*26*). Although control variables were limited (e.g., vehicle type was not included) and the model structure unsophisticated, this early research was influential in later studies. Bedard et al. aimed to use vehicle weight (although not vehicle type) as a control variable but ended up relying on wheelbase instead (since wheelbase is highly correlated with weight and gave them more precise results) (*5*). Farmer et al. did control for vehicle type and weight as well as the collision partner's type and weight (*4*). However, their model estimated only the probability of a severe or fatal injury outcome, by using a binary logistic regression model. Toy and Hammitt used the ratio of the vehicle curb weights as an explanatory variable in their two-vehicle crash model (*12*). Thus, they assumed that only the ratio of weights, rather than their absolute values, is what contributes to injury severity.

This work controls for the most valuable variables used by O'Donnell and Connor (*24*), along with vehicle weights, both for the primary vehicle and any collision partner. It also calibrates distinct models for single- and two-vehicle crashes, since these are distinctive crash types. Note that multivehicle crashes are first divided into several two-vehicle crashes in which the collision partner is defined as the first vehicle to crash into the observed vehicle.

MODEL STRUCTURE

On the basis of the strengths and limitations of the various models used in previous research, this study used the HOL model to study a variety of factors that influence injury severity. The general form of the HOL model can be explained via Equations 1 through 8.

Let y denote the occupant's observed injury severity level, y^* the latent (unobserved) injury severity measure, and $\mu_j (j = 1,2,3)$ the thresholds for injury severity, such that the following hold:

$$y = 0 \text{ (no injury)} \quad \text{if } y^* \leq 0$$

$$y = 1 \text{ (no visible injury, only pain reported)} \quad \text{if } 0 < y^* \leq \mu_1$$

$$y = 2 \text{ (nonincapacitating injury)} \quad \text{if } \mu_1 < y^* \leq \mu_2$$

$$y = 3 \text{ (incapacitating injury)} \quad \text{if } \mu_2 < y^* \leq \mu_3$$

$$y = 4 \text{ (death)} \quad \text{if } y^* > \mu_3$$

The latent injury severity measure y^* is obtained by using a linear equation:

$$y^* = x'\beta + \epsilon \tag{1}$$

where x is the set of factors explaining y^*, with associated parameters β, and the error term ϵ indicates the effect of all unobserved factors on y^*. If one defines $\mu_{-1} = -\infty$, $\mu_0 = 0$ and $\mu_j = +\infty$, then the probability of injury severity j for the ith observation can be written as the following (*16*):

$$\begin{aligned} P(y = j) &= P(\mu_{j-1} < y^* \leq \mu_j) \\ &= F\left(\frac{\mu_j - x_i\beta}{\sigma_i}\right) - F\left(\frac{\mu_{j-1} - x_i\beta}{\sigma_i}\right) \end{aligned} \tag{2}$$

where $F(\ )$ is the logistic distribution's cumulative distribution function and σ_i^2 is the variance of the random contribution of unobserved factors in the ith observation, parameterized to ensure its positivity, by using an exponential function. In other words,

$$F(x) = \left[1 + \exp(-x)\right]^{-1} \tag{3}$$

$$\sigma_i^2 = \left[\exp(Z_i\gamma)\right]^2 \tag{4}$$

where Z_i is the set of variables explaining the error term variance of the ith observation and γ is the associated parameter set. It can be seen here that an OL model, which assumes homoscedasticity, restricts γ to equal zero. For the model used in this work, the variance is parameterized as a function of speed limit [similar to O'Donnell and Connor's use of travel speed (*24*)], vehicle type, and vehicle curb weight. The use of speed limit in the variance specification is based on O'Donnell and Connor's use of travel speed (a variable that is missing in most crash observations used here), and vehicle type and weight are used because a great many unobserved vehicle features are connoted by these, including variables like stiffness and structure. (The effects of occupant gender and age also were tested in the variance specification but were then excluded because they were not statistically significant.) Coefficients can be estimated by using the method of maximum likelihood. For HOL, the likelihood function is (*16*)

$$L = \prod_{j=1}^{J} \prod_{i=1}^{n} \left[F\left(\frac{\mu_j - x_i\beta}{\sigma_i} \right) - F\left(\frac{\mu_{j-1} - x_i\beta}{\sigma_i} \right) \right]^{w_{ij}} \tag{5}$$

Here w_{ij} is the weight or expansion factor for the ith observation (i.e., occupant) experiencing injury severity level j. (Sample unit expansion factors are provided in the NASS CDS data set, in recognition that certain crashes are relatively underreported.)

As Greene indicated, in an ordered probit (or logit) model, the sign of any parameter β_i can clearly determine the marginal effect of variable x_i only on the extreme probabilities (in this case, the probability of no injury and the probability of a fatal injury) (*27*). The marginal effects on all other probabilities are ambiguous, since a shift in the distribution can cause the probability of intermediate response types to fall or rise, depending on the positioning of the average response. For an HOL model, this issue is complicated when the variable of interest affects not only the latent injury severity but also the variance. In an HOL model, the marginal effect of such a variable x_t across the sample, for the average observational case, can be written as follows:

$$\frac{\partial P(y = j)}{\partial x_t} = \left[f\left(\frac{\mu_j - \bar{x}\beta}{\bar{\sigma}} \right) - f\left(\frac{\mu_{j-1} - \bar{x}\beta}{\bar{\sigma}} \right) \right] \cdot \frac{\beta_t}{\bar{\sigma}} \cdot (\gamma_t \bar{x}_t - 1)$$
$$- \left[\mu_j f\left(\frac{\mu_j - \bar{x}\beta}{\bar{\sigma}} \right) - \mu_{j-1} f\left(\frac{\mu_{j-1} - \bar{x}\beta}{\bar{\sigma}} \right) \right] \cdot \frac{\gamma_t}{\bar{\sigma}} \tag{6}$$

where

x_t = variable of interest,
$\bar{x}_t$ = its weighted average across observational units,
$\bar{\sigma}$ = (weighted) mean variance across observations,
$\bar{x}$ = vector of (weighted) average values,
β_t = tth variable's coefficient for explaining y^*,
γ_t = that same variable's coefficient for explaining variance σ^2, and
$f(\ )$ = probability density function for the logistic distribution:

$$f(x) = \frac{\exp(-x)}{[1 + \exp(-x)]^2} \tag{7}$$

As Equation 6 suggests, the tth variable's marginal effect is related not only to its own, primary coefficient but also to its average value and the value of it variance-specifying coefficient. Therefore, even the marginal effect on the extreme probabilities cannot be inferred from simply the signs of the estimated primary parameters. Equation 6 must be used when determining the marginal effects of vehicle type, since these were used to specify the variance relation. If the variable of interest, x_t, explains only the injury severity measure, y^*, and not the variance, then its marginal effect simplifies to Equation 8. In this case, similar conclusions about those variables' marginal effects can be drawn as in the standard, homoscedastic OL model.

$$\frac{\partial P(y = j)}{\partial x_t} = -\left[f\left(\frac{\mu_j - \bar{x}\beta}{\bar{\sigma}} \right) - f\left(\frac{\mu_{j-1} - \bar{x}\beta}{\bar{\sigma}} \right) \right] \cdot \frac{\beta_t}{\bar{\sigma}} \tag{8}$$

The effects of binary variables on probabilities can best be obtained by comparing probabilities where the variable equals 1 and where it equals 0 (i.e., the base variable is used) with all other variables held at their average values (except in the case of other binary variables that share the same category with the variable under evaluation; of course, these are held at 0). For convenience, the effects of binary variables are also called marginal effects in this paper.

It can be seen from the preceding analysis that HOL models allow the distribution of unobserved factors to differ, providing more flexibility and realism than an OL model. As an example, the stiffness of SUVs may help protect occupants, but their added rollover potential can counter this effect, resulting in more outcome uncertainty. Such vehicle types then would be expected to exhibit higher variability in their latent injury severity measures, a feature permitted by HOL specifications. Because of this feature, HOL models allow extreme probabilities to be similarly affected (i.e., in the same direction) when variable values change.

DATA DESCRIPTION

The data set used in this paper come from the NASS CDS for 1998 through 2001. The NASS CDS collects crash data at 24 sites [also called primary sample units (PSUs)] in 17 states. All crashes selected are police reported, involving property damage or personal injury or both and at least one towed passenger car or light truck or van. Data are sampled in a stratified fashion, first among PSUs, then among police jurisdictions, and last among reported crashes, and together they represent just 0.05% of all police-reported crashes in the United States, less than most other national collected data sets. Each observation in the sample data is given a population expansion factor called a ratio inflation factor, which is the inverse of the probability of selecting that crash from crashes nationwide. This value is used as the observational weight in the likelihood function's (Equation 5) maximization.

It is important to note that CDS data are not totally unbiased. More severe crashes are more likely to be reported and thus entered into the CDS. Weights are estimated to try to account for these selection biases, but some statistical uncertainty remains. Moreover, different PSUs have different criteria for reporting their crash data (such as a minimum crash cost or severity). This causes some geographic heterogeneity in the data (*19*). Nonetheless, among all available data sets, the NASS CDS is the most appropriate one for this study because of its detailed information and comparatively unbiased sample. Farmer et al. (*4*) and Toy and Hammitt (*12*) also used the NASS CDS. Other, larger sample data sets either lack vehicle weight information [such as the NASS general estimates system (NASS GES) and the Highway Safety Information System] or focus on a particular crashes [such as the Fatal Accident Reporting System (FARS)]. These data sets may be preferable when the effect of vehicle weight is not concerned. For example, White (*28*) and Kockelman and Kweon (*19*) used NASS GES in their studies; Bedard et al. (*5*), Gayer (*29*), and Kahane (*6*) used FARS.

Information on vehicles and occupants were merged to produce an occupant-based data set. There are 18,609 occupant observations for two-vehicle crashes and 7,628 for one-vehicle crashes containing all required variables. These represent 53.6% and 77.8% of the NASS CDS sample data for such crash occupants, respectively. The dependent variable, injury severity, is missing in 6,036 occupant observations, accounting for a large percentage of the invalid observations. Other variables missing in significant numbers include occupant age and gender, seat belt use, curb weight, seat type, and weight of collision partner.

Less severe injuries and passenger cars as collision partners are slightly underrepresented in the data analyzed here. Bucket seat types are overrepresented in both models. Furthermore, because the NASS CDS does not provide curb weights for medium- and heavy-duty trucks, these are assumed to weigh 25,000 lbs here. Any overall bias in this assumption is expected to be largely picked up by the indicator variable used for medium and heavy trucks in the model's specification.

ANALYSIS OF RESULTS

It is necessary to compare the OL and HOL model results and select the preferred model before focusing on specific results for each of the explanatory variables used.

Comparison of OL and HOL Model Results

Explanatory variables for injury severity include vehicle, weather, roadway, and occupant information. Variance is explained by vehicle type, vehicle curb weight, and speed limit. Variable statistics are presented in Table 1. As noted, the models are estimated by using the method of maximum likelihood in LIMDEP. The results for both OL and HOL models are shown in Table 2. The existence of heteroscedasticity in one- and two-vehicle crashes are tested by using likelihood ratio (LR) tests, as follows (*27*):

$$\begin{aligned} \mathrm{LR}_{\text{one-vehicle}} &= -2\left(\ln L_{\text{restricted}} - \ln L_{\text{unrestricted}}\right) \\ &= -2\left[-8530.5 - (-8505.4)\right] \\ &= 50.3 > \chi^2_5 = 20.52 \end{aligned} \tag{9}$$

$$\begin{aligned} \mathrm{LR}_{\text{two-vehicle}} &= -2\left(\ln L_{\text{restricted}} - \ln L_{\text{unrestricted}}\right) \\ &= -2\left[-20265.8 - (-20099.3)\right] \\ &= 333.0 > \chi^2_{10} = 29.59 \end{aligned} \tag{10}$$

Thus for both types of crash, the null hypotheses $\gamma = 0$ are rejected at a 0.001 significance level, suggesting that heteroscedasticity exists in both crash types. Thus, the more flexible HOL specification is statistically preferred to the OL model.

As shown in Table 2, all explanatory variables (in both one-vehicle and two-vehicle crashes) result in similar OL and HOL estimates. But the HOL models also produce several statistically significant coefficients characterizing variance of the model's error term. These suggest that variance varies with vehicle weight, speed limit, and vehicle type. Those traveling in pickups on roads with higher speed limits experience greater variation in their injuries than others. This added uncertainty in injury outcomes may be due to greater diversity in truck designs and more potential for extreme crashes at higher speeds.

Table 3 further shows the difference of marginal effects in OL and HOL, by using the two-vehicle collision partner vehicle type as an example. (The primary vehicle type is held at its mean value, which means the figures presented in the table indicate an average effect of the given collision partner vehicle type.) For the OL model, as expected, the marginal effect on the probability of no injury has the same sign as the coefficient on the right-hand side of Table 2, whereas the probability of fatality has the opposite sign. In this model, all injury severity levels other than no injury experience the same direction of change as the probability of fatality. The OL model results suggest that SUVs, minivans, and pickups are more aggressive than cars of the same weight, everything else constant. The HOL model depicts things a little differently. Pickups are still shown to be more aggressive than cars. SUVs are also more aggressive, although the fatality probability decreases slightly. Minivans, which are built on car frames, are no more aggressive than cars. (Although they increase the probability of overall injury for occupants in their collision partners, the probabilities of incapacitating and fatal injuries are both lower.) This suggests that pickups and SUVs, which have raised bodies and often have a rigid frame, are more aggressively designed than cars and minivans, as pointed out by Newstead et al. (*30*), Kahane (*6*), and Gabler and Hollowell (*31*). Thus, recognition of heteroscedasticity due to collision partner's vehicle type has illuminated an interesting distinction that would not be visible in the less-flexible OL model.

Effects of Vehicle Weight and Type

In addition to the effects of the described collision partner vehicle type (since OL and HOL results differ on this point), the effects of (primary) vehicle type and weight of collision partner (in the case of two-vehicle crashes) are of great interest. Figure 1 shows the changes of injury severity probability (given that a crash has occurred) with respect to these variables. In one-vehicle crashes, occupants in heavier vehicles are estimated to sustain more severe injuries, but the effect of weight in one-vehicle crashes is less dramatic than that in two-vehicle crashes. In two-vehicle crashes, increasing vehicle weight is found to reduce all injury probabilities for occupants (*4*)—while raising those for occupants of collision partners. By considering both crashworthiness and aggressiveness effects of vehicle weight in both crash types (where 30% of crashes involve just one vehicle) and holding all other variables at their average values, a weight increase of 1,000 lb of all U.S. vehicles can be estimated. [Different from the study by Kahane (*6*), this vehicle weight increase occurs on all types of vehicles and on both primary and counterpart vehicles based on the fleet and crash-type proportions witnessed in the NASS CDS data set.] The models predict that the overall probability of injury or death will fall by 3%. Nonincapacitating and incapacitating injury probabilities are predicted to fall by 1% and 5%, respectively, whereas the probability of death is predicted to rise by 19%. Thus, the overall effect of increasing light-duty vehicle weights (by 33%) is almost negligible.

In one-vehicle crashes, minivans and pickups are estimated here to be less crashworthy, everything else constant (including weight). In contrast, SUVs are found to decrease the probability of occupant injury while increasing the probability of fatality. Similarly, Kockelman and Kweon found that pickups and SUVs are less safe than passenger cars in single-vehicle crashes (*19*). White found that occupants involved in single-vehicle crashes are more likely to be killed or seriously injured if they are driving a light truck rather than a car (*28*). Ulfarsson and Mannering also found that in single-vehicle accidents, pickup, SUV, and minivan drivers tend to sustain more severe injuries than drivers of passenger car (*15*). In two-vehicle crashes, all light-duty trucks (i.e., minivans, pickups, and SUVs) are predicted to result in more severe injuries for their occupants, that is, they are less crashworthy, after controlling for vehicle weight. At first glance, this conclusion may appear to be at odds with work by Krull et al. (*11*), Kockelman and Kweon (*19*), and Abdel-Aty (*21*); however, such research did not controlled for both vehicle weight and type simultaneously (nor for variables like seat type).

If all passenger cars were to become light-duty trucks (based on each vehicle type's own average weight and the crash-type proportions

TABLE 1 Variable Definitions and Statistics

Variable	Variable Description	One-Vehicle Crashes Mean	One-Vehicle Crashes Std. Dev.	Two-Vehicle Crashes Mean	Two-Vehicle Crashes Std. Dev.
CURBWGT#	Curb weight of the vehicle, in lbs	3,170	720.9	3,047	726.3
CAR	1 if the vehicle is a passenger car; 0 otherwise	Base variable for vehicle type			
MINIVAN#	1 if the vehicle is a minivan; 0 otherwise	0.039	0.193	0.087	0.283
SUV#	1 if the vehicle is an SUV; 0 otherwise	0.214	0.410	0.082	0.274
PICKUP#	1 if the vehicle is a pickup; 0 otherwise	0.127	0.333	0.093	0.291
PTNRVEHWGT*	Curb weight of the collision partner, in lbs			4,302	4,690
PTNRCAR	1 if the collision partner is a car; 0 otherwise	Base variable for partner vehicle type			
PTNRMINIVAN*	1 if the collision partner is a minivan; 0 otherwise			0.084	0.277
PTNRSUV*	1 if the collision partner is an SUV; 0 otherwise			0.116	0.321
PTNRPICKUP*	1 if the collision partner is a pickup; 0 otherwise			0.170	0.376
PTNRMDTHDT*	1 if the collision partner is a medium or heavy-duty truck; 0 otherwise			0.047	0.212
BUCKET	1 if the seat is a integral bucket; 0 otherwise	Base variable for seat type			
FOLDINGBUCKET	1 if the seat is a bucket with folding back; 0 otherwise	0.263	0.440	0.253	0.434
BENCHSEAT	1 if the seat of the occupant is a integral bench; 0 otherwise	0.072	0.258	0.077	0.267
SEPBENCH	1 if the seat is a bench with separate cushion; 0 otherwise	0.098	0.297	0.105	0.306
FOLDINGBENCH	1 if the seat is a bench with folding cushion; 0 otherwise	0.165	0.371	0.126	0.332
OTHERSEAT	1 if the seat is pedestal or box mounted; 0 otherwise	0.029	0.169	0.045	0.207
NOBELT	1 if the occupant does not use any belt; 0 otherwise	Base variable for seat belt usage			
LAPSHOU	1 if the occupant uses lap and shoulder belt; 0 otherwise	0.550	0.497	0.546	0.498
OTHEBELT	1 if the occupant uses shoulder only or lap only belt; 0 otherwise	0.204	0.403	0.316	0.465
GOODWEATHER	1 if the weather is good; 0 otherwise	Base variable for weather			
BADWEATHER	1 if the weather is adverse, including snowy, rainy, foggy and smoky; 0 otherwise	0.215	0.411	0.190	0.392
LIGHT	1 if the light condition is daylight; 0 otherwise	Base variable for light condition			
DARK	1 if the light condition is dark or dawn; 0 otherwise	0.543	0.498	0.263	0.440
SPDLIMIT#	Speed limit of the site (unit: mph)	44.6	14.4	40.5	10.3
SPDLIMITSQD	Square of the speed limit of the site (unit: mph^2)	2,194	1,364	1,749	888.9
NODIVISION	1 if the roadway is two-way yet not divided; 0 otherwise	Base variable for road division			
NONPOSITIVEDIV	1 if the roadway is divided by vegetation, water, trees, embankments, ravine; 0 otherwise	0.144	0.351	0.220	0.414
POSITIVEDIV	1 if the roadway is divided by manufactured barriers; 0 otherwise	0.125	0.331	0.090	0.287
ONEWAY	1 if the roadway is a one-way road; 0 otherwise	0.070	0.254	0.050	0.219
STRAIGHT	1 if the roadway is straight; 0 otherwise	Base variable for horizontal curve			
CURVRIGHT	1 if the roadway curves right; 0 otherwise	0.161	0.367	0.060	0.238
CURVLEFT	1 if the roadway curves left; 0 otherwise	0.266	0.442	0.053	0.224
LEVEL	1 if the roadway is level; 0 otherwise	Base variable for grade			
UPHILL	1 if the roadway is uphill; 0 otherwise	0.152	0.359	0.173	0.378
DOWNHILL	1 if the roadway is downhill; 0 otherwise	0.303	0.460	0.143	0.350
AGE	Occupant age (unit: year)	27.9	16.0	32.0	19.0
MALE	1 if male; 0 otherwise	Base variable for gender			
FEMALE	1 if female; 0 otherwise	0.384	0.486	0.513	0.500
FRONTLEFT	1 if seated in the driver seat (front left); 0 otherwise	Base variable for seat position			
FRONTRIGHT	1 if seated in the front passenger seat (front right); 0 otherwise	0.208	0.406	0.202	0.401
SECONDLEFT	1 if seated in the second row, left seat; 0 otherwise	0.076	0.264	0.081	0.273
SECONDRIGHT	1 if seated in the second row, middle or right seat; 0 otherwise	0.066	0.249	0.048	0.214
OTHERPOSITION	1 if seated in position other than the above and front left; 0 otherwise (including the third row and outside the pickups)	0.008	0.091	0.011	0.103

*This variable is also used in the heteroscedasticity specification for two-vehicle crashes.
#This variable is also used in the heteroscedasticity specifications for two-vehicle and one-vehicle crashes.

TABLE 2 Results of Ordered Logit and Heteroscedastic Ordered Logit Models

	One-Vehicle Crashes				Two-Vehicle Crashes			
	HOL		OL		HOL		OL	
Variable	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
Latent injury severity measure								
Constant	−2.046	−59.614	2.000	−63.340	2.519	55.737	0.786	35.129
CURBWGT	1.94E−04	32.252	1.21E−04	22.221	−6.93E−04	−98.055	−2.64E−04	−94.360
MINIVAN	−0.075	−0.939	0.195	3.469	0.495	30.737	0.243	37.886
SUV	−0.380	−51.719	−0.216	−33.173	0.532	40.957	0.256	39.280
PICKUP	0.295	18.818	0.437	33.059	0.059	3.550	0.087	12.330
PTNRVEHWGT	—		—		2.48E−04	52.123	7.47E−05	49.906
PTNRSUV	—		—		0.596	64.880	0.311	64.635
PTNRMINIVAN	—		—		0.395	36.478	0.177	29.483
PTNRPICKUP	—		—		0.214	25.773	0.270	74.633
PTNRMDTHDT	—		—		−5.539	−51.866	−1.411	−41.653
FOLDINGBUCKET	0.111	18.202	0.081	14.477	−0.128	−19.161	−0.071	−20.609
BENCHSEAT	−0.570	−48.939	−0.499	−46.746	0.105	4.983	0.047	4.932
SEPBENCH	0.370	29.069	0.367	31.345	0.786	60.730	0.387	61.881
FOLDINGBENCH	−0.416	−31.939	−0.309	−26.858	−0.115	−6.671	−0.082	−10.167
OTHERSEAT	−0.362	−4.170	−0.345	−5.579	−0.041	−1.706	−0.026	−2.398
LAPSHOU	−1.422	−228.349	−1.285	−233.341	−1.298	−153.502	−0.663	−153.988
OTHEBELT	−1.026	−143.930	−0.909	−141.373	−1.526	−172.436	−0.742	−164.853
BADWEATHER	−0.949	−97.003	−0.877	−100.323	−0.795	−116.375	−0.384	−116.469
DARK	−0.125	−25.523	−0.078	−17.472	0.475	65.583	0.232	64.447
SPDLIMIT	0.062	57.742	0.065	64.518	−0.099	−52.035	−0.038	−38.873
SPDLIMITSQD	−5.11E−04	−42.371	−5.12E−04	−46.578	1.46E−03	63.909	6.49E−04	58.161
NONPOSITIVEDIV	0.610	53.738	0.547	53.346	−0.170	−24.687	−0.099	−28.106
POSITIVEDIV	−0.056	−4.939	−0.084	−8.386	−1.378	−105.902	−0.696	−115.116
ONEWAY	0.341	24.982	0.235	19.542	−0.346	−18.810	−0.228	−26.204
CURVRIGHT	0.323	31.568	0.252	27.606	0.669	48.656	0.362	58.832
CURVLEFT	0.564	69.939	0.500	70.199	0.909	76.342	0.460	86.546
UPHILL	0.071	8.176	0.047	5.828	−0.322	−41.688	−0.148	−41.358
DOWNHILL	−0.169	−20.230	−0.149	−19.668	0.642	64.723	0.353	73.510
AGE	1.66E−02	77.145	1.53E−02	80.867	1.13E−02	57.163	5.79E−03	61.760
FEMALE	0.681	150.887	0.623	151.267	0.645	117.495	0.316	113.742
FRONTRIGHT	−0.143	−40.959	−0.151	−47.495	0.086	14.527	0.030	9.775
SECONDLEFT	−0.682	−53.686	−0.670	−58.016	−0.998	−48.286	−0.467	−49.399
SECONDRIGHT	−0.630	−50.511	−0.658	−58.010	−1.042	−35.158	−0.513	−40.396
OTHERPOSITION	−0.078	−0.540	−0.131	−1.255	−0.252	−7.539	−0.025	−1.602
Variance								
CURBWGT	−3.59E−05	−2.368	—	—	7.18E−05	5.561	—	—
MINIVAN	0.303	3.814	—	—	−0.006	−0.154	—	—
SUV	0.141	3.152	—	—	−0.040	−0.988	—	—
PICKUP	0.307	5.832	—	—	0.104	2.491	—	—
SPDLIMIT	3.06 E−03	3.266	—	—	8.61E−03	9.681	—	—
PTNRVEHWGT	—	—	—	—	3.07E−05	2.862	—	—
PTNRSUV	—	—	—	—	−0.100	−3.134	—	—
PTNRMINIVAN	—	—	—	—	−0.186	−5.089	—	—
PTNRPICKUP	—	—	—	—	0.214	6.800	—	—
PTNRMDTHDT	—	—	—	—	−0.262	−1.085	—	—
Threshold								
μ_0	0.000	—	0.000	—	0.000	—	0.000	—
μ_1	0.713	24.422	0.642	34.920	2.257	31.208	1.118	70.526
μ_2	2.133	29.339	1.911	54.523	4.228	32.331	2.070	82.932
μ_3	5.264	26.744	4.639	41.769	11.764	26.891	5.410	44.628
Number of observations	7,628				18,609			
LRI	0.237		0.235		0.257		0.251	

LRI = likelihood ratio index.

TABLE 3 Marginal Effects of Collision Partner's Vehicle Type

		Marginal Effect (Change of Probabilities Versus Cars)				
Model Type	Vehicle Type	No Injury	Possible Injury	Nonincapacitating Injury	Incapacitating Injury	Fatal Injury
HOL	Minivan	−0.0439	0.0519	0.0097	−0.0162	−0.0014
	SUV	−0.0734	0.0435	0.0238	0.0068	−0.0006
	Pickup	−0.0343	−0.0279	0.0093	0.0473	0.0056
	HDT&MDT	0.4110	−0.2168	−0.1097	−0.0822	−0.0023
OL	Minivan	−0.0434	0.0153	0.0141	0.0135	0.0006
	SUV	−0.0767	0.0253	0.0252	0.0251	0.0011
	Pickup	−0.0664	0.0224	0.0217	0.0214	0.0010
	HDT&MDT	0.2646	−0.1324	−0.0727	−0.0572	−0.0023

NOTE: Probabilities are calculated while evaluating all other variables at their average values. HDT = heavy-duty truck; MDT = medium-duty truck.

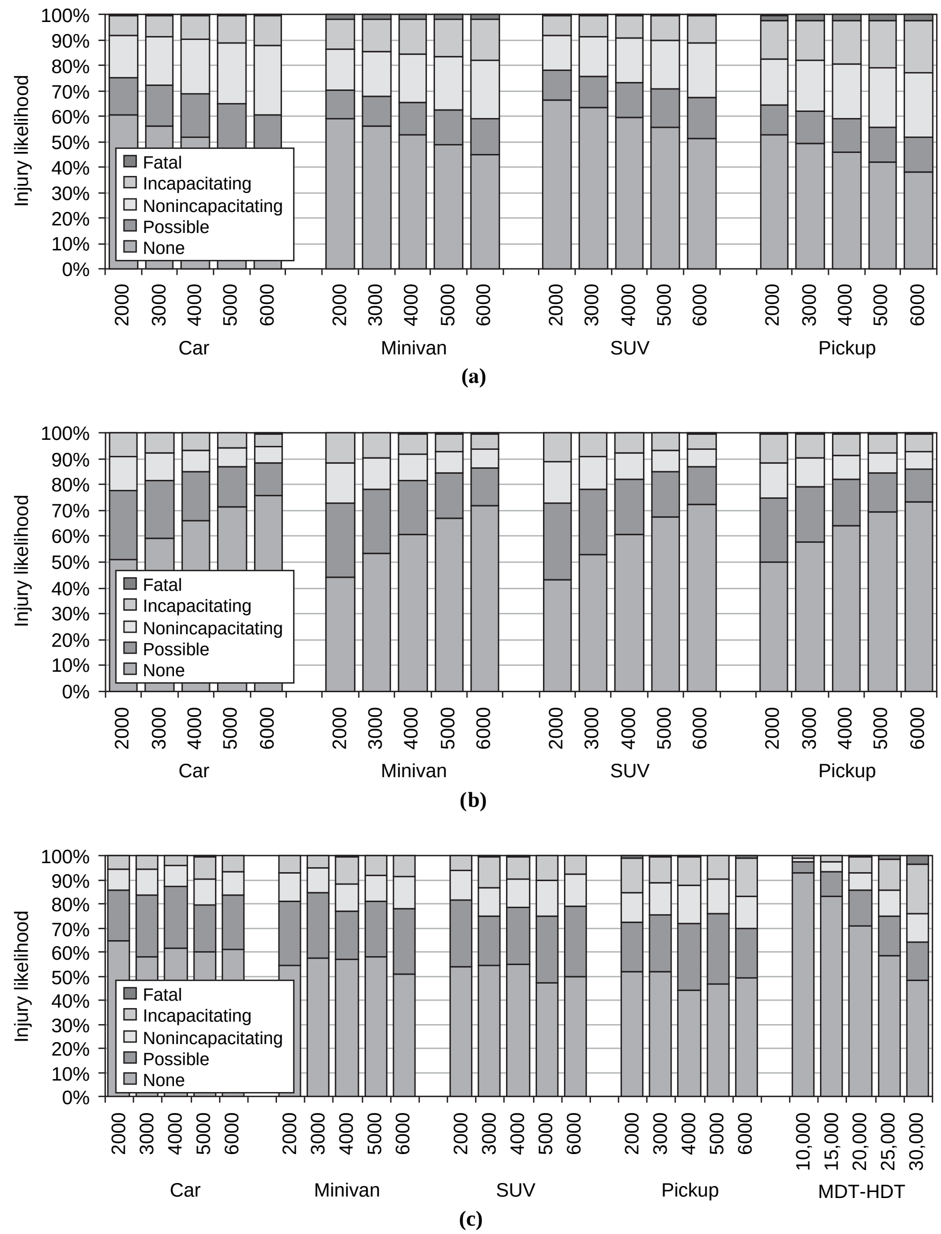

FIGURE 1 Probabilities of injury by vehicle type and weight in (*a*) one-vehicle crashes by type and weight, (*b*) two-vehicle crashes by type and weight of primary vehicle, and (*c*) two-vehicle crashes by type and weight of collision partner vehicle.

witnessed in the NASS CDS data set), the overall probability of sustaining some kind of injury (even those that are not visible) following a crash is predicted to increase by 3%. Among these, the incapacitating injury is expected to rise by 25% and fatalities by a startling 79%. The results suggest that lighter vehicles reduce, rather than increase, the probability of death. Of course, it is difficult to believe that lighter vehicles are indeed safer if the only variable that changes is weight. In reality, vehicle weight is probably correlated with design variables not controlled for here (such as bumper design and vehicle interior padding). Thus, the results simply may imply that vehicle design is more important than weight. This implication is consistent with manufacturer Honda's stated position, although Honda is a notable dissenter in the automotive industry (*3*). It also suggests that policy makers should not be so concerned about fatality rates as a result of more stringent fuel economy legislation; they should instead be concerned about vehicle design. This conclusion is consistent with that by Greene and Keller (*32*).

In addition, it should be noticed that vehicle weight and type are often correlated with driver characteristics, such as travel speed choice and other aggressive behaviors. Thus a vehicle's crashworthiness and aggressiveness, as estimated here, also may reflect driver attributes. Moreover, some vehicles may be less likely to be crash involved, because of better brakes or other design attributes, and so overall risk may differ from risk conditioned on having been crash involved. Kweon and Kockelman present crash rate and risk estimates by vehicle and driver type (*20*). Finally, the variable of vehicle age was controlled for in initial models and found to be statistically insignificant; its results are not presented here.

Seating and Seat Belts

Vehicle equipment is important in protecting crash victims. The model results suggest that bench-type seats with separate cushions (*33*) are the least safe in both one-vehicle and two-vehicle crashes. This may be because they are more likely to collapse in crashes. Benches with folding backs, however, are estimated to be most protective, perhaps because they are neither as stiff as integral seats nor as fragile as seats with separate cushions, as suggested by Prasad et al. (*34*) and Burnett et al. (*8*). As expected, seat belts play a key role in protecting occupants. In two-vehicle crashes, with lap and shoulder belts working together, the probability of being injured decreases by 36.3% and that of being killed decreases by 47.3%, when compared with not wearing a seat belt. The effect of wearing a lap-only or shoulder-only belt is estimated to be statistically equivalent to wearing a lap-and-shoulder belt. The effect of seat belts is more pronounced in one-vehicle crashes. Wearing lap-and-shoulder belts is estimated to decrease the probability of being injured by a striking 90.2% and the probability of being killed by 71.9%. (Lap-only or shoulder-only belts are estimated to decrease the probability of being injured by 65.7% and the probability of being killed by 60%, which is still striking.) The general effect of seat belt for all crash types is that lap-and-shoulder belts are better than lap-only or shoulder-only belts, especially for preventing slight injuries. This result is consistent with the results of Huelke et al. (*35*) and others.

Roadway Design and Environmental Factors

Roadway features, including speed limits, geometric characteristics, and traffic safety measures, affect injury severity by influencing the manner of the crash (such as speed and collision type). Environmental factors, such as weather and lighting, also can play important roles.

As expected, the results indicate that in two-vehicle crashes, roads with higher speed limits have a higher proportion of fatal crashes. This change is clearer at higher speed limits. When the speed limit changes from 35 to 45 mph, the probability of being injured increases by 0.03 (or 4.7%) and the fatality probability increases by 0.001 (or 86.6%). When the speed limit changes from 65 to 75 mph, the probability changes are 0.09 (or 19.7%) and 0.01 (or 110.1%). It is interesting to find that in one-vehicle crashes, the probability of being injured is the highest when the speed limit is 60 mph. Over this speed limit, the probability of injury decreases. However, the fatality probability increases with the speed limit, but the effect of speed limit is not as significant as that in a two-vehicle crash. When the speed limit increases from 65 mph to 75 mph, the probability of being killed increases by only 0.0007 (or 6.1%). Zhang et al. (*36*), Krull et al. (*11*), and Khattak et al. (*18*) all found that higher speed limits are associated with more severe injuries. This work shows results consistent with theirs. However, the speed limits are correlated with a host of design factors that permit higher speed limits, such as wider lanes and shoulders and less horizontal and vertical curvature. These better design features counteract the speed limit effect, especially for one-vehicle crashes, biasing its coefficient toward zero. Speed limits also may be associated with certain use variables, such as AADT per lane and heavy-duty truck use. Thus, it is difficult to estimate the true effect of speed limits, everything else constant, without controlling for all such variables.

Adverse weather is estimated to be safer for occupants. In two-vehicle crashes, bad weather decreases the probability of being injured by 0.09 (16.4%) and the probability of being killed by 0.0007 (or 32.5%). In one-vehicle crashes, its effect is more significant. This can be attributed to more cautious driver behavior during bad weather, including lower speeds. This conclusion is consistent with that of Khattak et al. (*17*). However, Zhang et al. found that snowy weather increases severity (*36*), and Dissanayake and Lu did not find weather to be statistically significant (*13*). Lack of light shows different effects in the two types of crashes. It decreases the severity in one-vehicle crashes, consistent with the work by Krull et al. (*11*), but increases the injury severity in two-vehicle crashes. In general, the lack of light results in greater injury severity. This is consistent with results of Khattak et al. (*18*) and Abdel-Aty (*21*).

Ideally, one would control for degree of curve, as well as vertical grade, but these variables are not provided in the NASS CDS data set. Nevertheless, related variables are included and controlled for here. For example, the presence of horizontal curvature increases injury severity risk. This is as expected and is consistent with work by Dissanayake and Lu (*13*) and Abdel-Aty (*21*). Evidently, a leftward curve is more dangerous than a rightward curve, in terms of any resulting injuries. Compared to a straight road section, a leftward curve increases the fatality probability by 56.7%, and a rightward curve increases the fatality probability by 39.2%. One-vehicle crashes show similar results. Whereas prior studies did not differentiate between uphill and downhill grades, Dissanayake and Lu found that grades are associated with more severe injuries (*13*). Here, after distinguishing uphill–downhill and one-vehicle–two-vehicle crashes, it is found that grade plays different roles in different circumstances. In two-vehicle crashes, downhill grades are associated with more severe injury, increasing the injury probability by 13.3% and fatality probability by 37.3%. Although uphill grades result in less severe injury, their effect is only half that of downhill grades. In one-vehicle crashes, however, the results suggest that uphill and downhill grades have no practically significant effects.

Roadway dividers and medians are estimated to decrease injury severity in two-vehicle crashes. Manufactured barriers are estimated to be the most effective, decreasing the probability of fatality by 0.001, or 53.7%. Use of vegetation, water, embankments, or ravines is not significantly better (in a practical sense) than no division. In one-vehicle crashes (which are largely run-off-the-road crashes), only manufactured barriers are estimated to decrease injury severity, and then only slightly. Other dividers and one-way roads are both estimated to increase injury severity, perhaps by offering little or no assistance to drivers who lose control of their vehicles.

Occupant Characteristics

As occupant age increases, so does injury severity. However, the effect of age is not as important as might be expected. In two-vehicle crashes, a 10-year increase in age results in about a 2% increase in injury probability and a 6% increase in fatality probability. In one-vehicle crashes, the effect of age is a little stronger but is also limited to only about 8% and 16%, respectively. This may be because older people often compensate for their fragility and slower reaction times by driving more cautiously (*13*). Women are more likely to sustain severe injuries than men. In two-vehicle crashes, a female's probability of being injured is 0.08 (12.4%) higher than a male's, and her fatality probability is 37.5% higher. In a one-vehicle crash, the effect is more dramatic. The gender effect is about twice that in a two-vehicle crash. Nearly all previous works found that females or older occupants or both are more prone to injury (*4, 36, 13, 5, 17, 19, 15*). Thus, this paper's results are consistent with their findings. It should be noted, however, that control variables can proxy for unobserved variables, such as driver risk aversion. For example, minivan drivers may differ from pickup drivers in multiple, immeasurable ways that affect outcome severity; these effects are statistically ascribed to the vehicle type variables, biasing their values. In the case of minivans, it may make them appear safer than they are, all things constant, if the drivers and their occupants take extra precautions.

In one-vehicle crashes, the driver's seat appears to be the most dangerous place to sit, although alert drivers should have a strong self-preservation instinct. The right seat in the front row and other positions (in the back of a pickup, for example) are estimated to be a little safer than the driver's position, but the differences are not statistically significant. In two-vehicle crashes, because of side- and rear-impact crashes, the right seat in the front row and other positions are slightly more dangerous than the driver's position. In both types of crash, the second row is much safer than the front row. The probability of being killed while seated in the second row is about 40% lower than while seated in the first row. When considering all crash types, the driver's position is generally the most dangerous place in a crash, consistent with Huelke and Compton's results (*9*).

CONCLUSIONS

This study of crash severity applies a relatively novel methodology, the heteroscedastic ordered logit, while controlling for a variety of relevant design, speed, vehicle, occupant, and environmental variables. It empirically distinguishes a vehicle's type from its weight for injuries endured not just by its own occupants but also the occupants of crash partners. Related studies, by Kockelman and Kweon (*19*) and Abdel-Aty (*21*), did not control for vehicle weight.

The results suggest that both the revocation of the national maximum speed limit in 1995 and the boom in sales of light-duty trucks may have contributed to the greater injury severity in recent years. In particular, SUVs and pickups are estimated to be more aggressive but no more crashworthy than cars after vehicle weights are controlled for. Notably, overall increases in the weight of the vehicle fleet are not found to significantly affect crash severity. This is an important point, since legislators, auto manufacturers, and others often resist efforts to increase fuel economy on the assumption that crash severities will increase. Of course, injury severity is influenced by a variety of other factors, including roadway design, environmental factors, and occupant characteristics. The many quantitative results provided here should be useful for auto manufacturers, highway engineers, policy makers, and travelers for providing, and experiencing, safer travel.

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