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Analysis of large truck crash severity using heteroskedastic ordered probit models

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ABSTRACT

Long-combination vehicles (LCVs) have significant potential to increase economic productivity for shippers and carriers by decreasing the number of truck trips, thus reducing costs. However, size and weight regulations, triggered by safety concerns and, in some cases, infrastructure investment concerns, have prevented large-scale adoption of such vehicles. Information on actual crash performance is needed. To this end, this work uses standard and heteroskedastic ordered probit models, along with the United States' Large Truck Crash Causation Study, General Estimates System, and Vehicle Inventory and Use Survey data sets, to study the impact of vehicle, occupant, driver, and environmental characteristics on injury outcomes for those involved in crashes with heavy-duty trucks. Results suggest that the likelihood of fatalities and severe injury is estimated to rise with the number of trailers, but fall with the truck length and gross vehicle weight rating (GVWR). While findings suggest that fatality likelihood for two-trailer LCVs is higher than that of single-trailer non-LCVs and other trucks, controlling for exposure risk suggest that total crash costs of LCVs are lower (per vehicle-mile traveled) than those of other trucks.

1. Introduction

Heavy-duty trucks (or HDTs, defined as trucks with gross vehicle weight rating [GVWR] over 10,000 lbs) are critical to freight movements around the globe. Larger trucks can increase economic productivity by increasing cargo capacity per trip. This is believed to result in reduced overall transportation and fuel costs and emissions due to fewer truck trips (Caltrans, 2009). As a result, use of long-combination vehicles (LCVs) is increasing, both in terms of total vehicle miles traveled (VMT) as well as proportion of vehicles on U.S. and Canada's highways (Abdel-Rahim et al., 2006). The United States defines LCVs as HDTS with GVWRs exceeding 80,000 lbs and having two or more trailers, with at least one such trailer longer than 28 ft.[1] In the U.S. and elsewhere, truck size and weight regulations, in large part motivated by safety concerns, have greatly limited the large-scale adoption of larger vehicles. The 1991 Intermodal Surface Transportation Efficiency Act (ISTEA) froze LCV operations on interstates to only those authorized by state governments before June 1, 1991. Currently, operation of three LCV configurations[2] is permitted on designated routes in twelve states: Alaska, Arizona, Colorado, Idaho, Indiana, Kansas, Montana, Nevada, North Dakota, Oklahoma, South Dakota and Utah. Other, specific configurations are permitted on selected routes in six other states (AASHTO, 1995).

Identifying factors which affect large-truck safety is essential for developing policies and regulations that enable LCV operations without compromising safety and efficiency. The number of large trucks involved in fatal and non fatal crashes increased by 5.9% from 2004 to 2007 (FMCSA, 2009), while VMT for these vehicles increased by 135% (FMCSA, 2009). In general, analysis of LCV safety relative to other heavy-duty trucks (HDTs) has been difficult, due to a lack of data involving LCVs (Craft, 1999; GAO, 1992; USDOT, 2000).

This work examines hundreds of factors affecting crash severity for persons involved in HDT crashes by analyzing records in the recent Large Truck Crash Causation Study Data (LTCCS), provided by the U.S. Federal Motor Carrier Safety Administration (FMCSA) and National Highway Traffic Safety Administration (NHTSA). Standard ordered probit and heteroskedastic ordered probit (OP and HOP) models are used to illuminate the impact of various truck, environmental and occupant characteristics on injury outcomes. HOP

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[1] In Canada, LCVs are defined as HDTs with two or more trailers and total length greater than 25 m (about 82 ft).

[2] The three LCV configurations operating in the U.S. are the Rocky Mountain Double (two trailers, with the first 48 ft long and second trailer 28.5 ft long), the Turnpike Double (two 48′ trailers), and the Triple (three 28.5′ trailers).

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models offer greater model flexibility (over standard OP models), since they capture the effect of crash characteristics on the variance or uncertainty in crash severity.

The next section provides a detailed overview of related research and motivates the need for this work. The model structure of the OP and HOP models is then discussed, along with formulae for calculating marginal effects of control variables and data sets used. Finally, model results and conclusions are provided.

2. Literature review

Researchers have adopted two approaches to the study of large truck and LCV safety. The first approach emphasizes operational characteristics and large truck design requirements, as compared to other trucks and roadway geometry, in order to anticipate real-world safety impacts (Caltrans, 1983; Debauche and Decock, 2007; Glaeser et al., 2006; Hanley and Forkenbrock, 2005; Harkey et al., 1996, Knight et al., 2008 and Renshaw, 2007). The second approach to large truck and LCV safety evaluation involves analysis of actual crash rates and outcomes, in order to identify general trends and relationships.

A number of studies have examined LCV crash rates. For instance, the USDOT (2000) concluded that trucks pulling more than two trailers are likely to be involved in 11% more crashes per mile traveled than single trailer trucks, when both trucks are operated under similar conditions (USDOT, 2000). Forkenbrock and Hanley (2003) found similar results under difficult driving conditions, including darkness, snow, and moderate traffic volumes on high-speed facilities. However, most studies suggest just the opposite. Campbell and Pettis (1989) surveyed 12 western states where LCV operations were permitted finding that LCV crash rates were lower, possibly due to operational restrictions on LCVs (such as the routes LCVs are permitted). Likewise, using the general estimates system (GES) data from 1989 to 1993, Wang et al. (1999) concluded that combination trucks enjoy significantly lower crash rates as compared to passenger vehicles and single-unit trucks (at rates of 226 combination truck crashes per 100 million miles traveled, versus 556, 416, and 289 for passenger vehicles, light-duty trucks, and single-unit trucks, respectively).

In a Dutch study, Debauche and Decock (2007) found that longer heavier vehicles (LHVs)[3] have similar levels of safety compared to heavy goods vehicles (HGVs)[4]–and slightly lower fatal injury crash rates. In addition, motorists apparently do not perceive any difference in safety of LHVs versus HGVs (Debauche and Decock, 2007). In Sweden, Vierth et al. (2008) concluded that the increase in accident risk due to the presence of longer trucks is not statistically significant and is offset by reductions in truck-miles (thanks to bigger cargos). Using Canadian data, Woodrooffe (2001) also found that LCVs enjoy low crash rates compared to all other vehicle classes. Similar conclusions were drawn by Montufar et al. (2007) for Canada. This work further concluded that injury and fatality rates of LCV crashes were lowest, and driver actions such as improper turning and lane change maneuvers and unsafe roadway conditions such as presence of snow, ice, slush, or rain were major causes of LCV related incidents (similar LCV crash causes were noted by Abdel-Rahim et al. (2006)). Of course, LCVs carry more cargo, so their crash rate per *ton-mile* can be even lower, relative to other heavy-duty trucks.

While crash rates may be significantly lower, LCVs and combination trucks have been found to result in higher casualty rates, per crash (Vierth et al., 2008 and Zaloshnja et al., 2000), and higher crash costs per incident (Wang et al., 1999, Zaloshnja et al., 2000, Zaloshnja and Miller, 2004; Zaloshnja and Miller, 2007). Nonetheless, Zaloshnja and Miller (2004) concluded that the lower crash rates of LCVs outweigh their higher crash costs, making LCVs safer per vehicle-mile traveled than other HDTs.

In the United Kingdom, Knight et al. (2008) found that 18.3% of traffic fatalities involved one HGV, even though they accounted for less than 6% of VMT. The three main factors affecting fatal outcome likelihood were found to be collision speed, mass of the two vehicles, and type of impact. Of course, the higher the collision speed, the more severe the crash. The likelihood of death for an HGV occupant is low, as long as the truck can absorb some of the crash impact (as is the case with most HGV-passenger car accidents). Knight et al. (2008) noted that the presence of Collision Mitigating Braking Systems (CMBS) having the potential to reduce heavy vehicle crash frequencies by up to 75%, and an even greater percentage for LHVs (Grover et al., 2007 and Knight et al., 2008).

By extrapolating the UK casualty rate data, Knight et al. (2008) concluded that casualty risks will increase with the number of axles. However, they acknowledge that the methodology they adopted significantly overestimates LHV risks. No trends were observed when fatality rates were extrapolated over gross vehicle weights. They also concluded that LHVs are more likely to be involved (around 5% to 10% more) in severe accidents as compared to standard trucks, assuming that no additional safety measures are employed in LHV use.

Recently, Knipling (2008) used the U.S.'s Large Truck Crash Causation Study (LTCCS), which contains information on 963 crashes involving 1241 trucks between 2001 and 2003, to compare combination truck and single-unit truck crashes. They examined 44 variables characterizing crash type, driver characteristics, driving environment and vehicle type. The percentage of crashes in dark conditions was found to be three times higher for combination trucks when compared to single-unit trucks.

Of course, LCVs do not always operate under the same conditions as other HDTs. For instance, LCV drivers are usually better-trained and have more experience than other HDT drivers in Canada and the U.S. (Abdel-Rahim, 2009 and Regehr, 2009). In addition, certain LCV operations may favor night time travel, and LCV use is often prohibited during times of heavy congestion in large Canadian cities (Regehr, 2009 and Woodrooffe, 2009). Abdel-Rahim (2009) has suggested that many U.S. states prohibit LCV use in bad weather conditions, and often restrict their use to routes with the most ideal geometric designs (such as interstate highways).

In general, no study has been able to conclusively determine whether larger trucks decrease safety levels overall. Much analysis has been based on simple rate comparisons and univariate or bivariate cross-tabulations. This paper uses ordered probit models to analyze injury severity for crashes involving at least one HDT (i.e., trucks with GVWR over 10,000 pounds). In addition, simulated outcomes are generated and combined with crash cost and HDT crash rate data to examine exposure risk of LCVs versus other HDTs. Ordered probit models have been used to analyze crash severity of automobile crashes (Abdel-Aty, 2003, Khattak et al., 1998, 2002; Khattak and Rocha, 2003; Kockelman and Kweon, 2002; Kweon and Kockelman, 2003), with O'Donnell and Connor (1996) and Wang and Kockelman (2005) using heteroskedastic ordered probit and logit models to analyze injury severity. The next section describes the model specification used in this study.

3. Model structure

A standard ordered probit (OP) model assumes that ordinal discrete responses can be modeled using a latent continuous variable expressed as a function of explanatory variables and an error term,

[3] LHVs are vehicles longer than 54 ft. and heavier than 44 metric tonnes (RoadTransport, 2009).

[4] HGVs are those vehicles weighing more than 3500 kg, or 7714 lbs (ERSO, 2009).

as follows:

$$U_i = X_i'\beta + \varepsilon_i \quad \forall i = 1, \ldots, N \tag{1}$$

where i is an index for an observation or individual, U_i represents the latent continuous dependent variable, X_i is vector of explanatory variables, β is a column vector of coefficients (to be estimated), and ε_i is an error term representing all unobserved characteristics affecting the crash outcome. In OP models, all values are modeled as i.i.d. normal random variables, with zero mean and variance σ^2.

The observed variable y_i for the ith observation can take ordinal discrete values ranging from 1 to S. The observed variable y_i is related to the continuous latent variable U_i as follows:

$$y_i = s \text{ if } \mu_{s-1} < U_i < \mu_s \quad s = 1, \ldots, S \tag{2}$$

where μ_s denotes the boundary points or thresholds for the latent continuous variable U_i such that $\mu_0 < \mu_1 < \ldots < \mu_S$. Since latent variables can assume any real numbered value, the first and last thresholds are set to $\pm\infty$ (i.e., $\mu_0 = -\infty$ and $\mu_S = \infty$). For the purpose of statistical identification, two other model parameters must be fixed as well. In this case, the second and third threshold parameters are set to 0 and 1 (i.e., $\mu_1 = 0$ and $\mu_2 = 1$). The probability of observed variable y_i taking an outcome value s is given by:

$$P(y_i = s) = \Phi\left(\frac{\mu_s - X_i'\beta}{\sigma}\right) - \Phi\left(\frac{\mu_{s-1} - X_i'\beta}{\sigma}\right) \tag{3}$$

where $\Phi(\cdot)$ represents the standard-normal cumulative distribution function.

In many cases, error terms may not be homoskedastic, and their variance may be parameterized as a function of covariates. In such cases, a heteroskedastic ordered probit (HOP) model is used, where the variance of observation i's error term, σ_i^2, is expressed as follows:

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

In the above equation, Z_i and γ represent vectors of explanatory variables and their associated coefficients, respectively. The probability of observed variable y_i taking an outcome value s is given by:

$$P(y_i = s) = \Phi\left(\frac{\mu_s - X_i'\beta}{\sigma_i}\right) - \Phi\left(\frac{\mu_{s-1} - X_i'\beta}{\sigma_i}\right) \tag{5}$$

The likelihood function of either model (OP or HOP) can be written as shown below:

$$L = \prod_{i=1}^{N}\left[\sum_{s=1}^{S}\delta(y_i = s)\left(\Phi\left(\frac{\mu_s - X_i'\beta}{\sigma_i}\right) - \Phi\left(\frac{\mu_{s-1} - X_i'\beta}{\sigma_i}\right)\right)\right]^{w_i} \tag{6}$$

where w_i represents the population expansion factor (or crash-record weight, as provided by the LTCCS data) for the ith observation, and $\delta(A)$ is an indicator variable taking a value of 1 if event A is true and 0 otherwise. In the OP case, $\sigma_i = \sigma \forall i$.

This paper uses Bayesian techniques to estimate the two models. Denoting the set of independent variables as X and the set of response variables as Y, the Bayesian posterior distribution is written as follows (Gelman et al., 2004):

$$p(\beta,\ \gamma,\ \mu\, Y|,\ X) \propto p(Y|\ \beta, \gamma,\ \mu,\ X)\pi(\beta,\ \gamma,\ \mu) \tag{7}$$

where $p(Y|\ \beta, \gamma, \mu, X)$ represents the likelihood function (shown in Eq. (6)) and $\pi(\beta, \gamma, \mu)$ is the prior distribution of model parameters (reflecting the analyst's prior beliefs). In the standard Bayesian construction of the probit model (see, e.g., Albert and Chib, 1993 and McCulloch and Rossi, 1994), latent variables, U_i, are assumed to be random (nuisance) parameters to be estimated. In this context, the likelihood function can be rewritten as follows:

$$L = \prod_{i=1}^{N}[\delta(\mu_{y_i-1} < U_i < \mu_{y_i})\pi(U_i|\beta, \sigma_i, X_i)]^{w_i} \tag{8}$$

Here, $\delta(\mu_{y_i-1} < U_i < \mu_{y_i})$ takes a value of 1 if U_i is between μ_{y_i-1} and μ_{y_i}, and $\pi(U_i|\beta, \sigma_i, X_i)$ represents our prior density of U_i (i.e., a normal with mean $X_i'\beta$ and variance σ_i^2). Using this notation, the posterior density of model parameters can be rewritten:

$$p(U, \beta, \sigma_i, \mu|Y, X) \propto \prod_{i=1}^{N}[\delta(\mu_{y_i-1} < U_i < \mu_{y_i})\pi(U_i|\beta, \sigma_i, X_i)]^{w_i} \times \pi(\beta, \sigma_i, \mu) \tag{9}$$

The prior distributions of parameters are assumed independent of one another such that $\pi(\beta, \sigma_i, \mu) = \pi(\beta)\pi(\sigma_i)\pi(\mu)$. The prior for β is taken to be normal with mean $\bar{\beta}$ and covariance matrix Σ_β and the prior on μ is taken to be non-informative (i.e., proportional to 1). In the case of the OP model, the prior on σ^2 is inverse gamma with shape and scale parameters q and r, and in the case of the HOP model, the prior on γ is taken to be normal with mean $\bar{\gamma}$ and covariance matrix Σ_γ.

Bayesian estimation for both model specifications proceeds by drawing each set of parameters from their conditional posterior distribution via a four-step Gibbs sampler as follows:

Step 1: Draw $U_i|\beta, \sigma_i, \mu, X_i, Y_i \forall i$
Step 2: Draw $\beta|U, \sigma, \mu, X, Y$
Step 3: Draw $\mu|U, \beta, \sigma, X, Y$
Step 4: Draw $\sigma_i|U_i, \beta, \sigma_i, X_i, Y_i \forall i$

For latent variable, U_i, the conditional posterior distribution is truncated normal with mean $X_i'\beta$, variance σ_i^2, and lower and upper bounds of μ_{y_i-1} and μ_{y_i}.

The conditional posterior distribution of β can be written as follows:

$$p(\beta|U, \sigma, \mu, X, Y) \propto \Pi_{(i=1)}^{N}[\pi(U_i|\beta, \sigma_i, X_i)]^{w_i}\pi(\beta) \tag{10}$$

Since $\pi(U_i|\beta, \sigma_i, X_i)$ and $\pi(\beta)$ are both normal densities, it can be shown through some simple manipulation that β is distributed normally with mean given by C and covariance matrix given by D, where C and D are defined as follows:

$$C = D(X'WU + \Sigma_\beta^{-1}\bar{\beta}) \tag{11}$$

$$D = (X'WX + \Sigma_\beta^{-1}\bar{\beta})^{-1} \tag{12}$$

Here, W is a matrix with off-diagonal elements of zero and diagonal elements equal to w_i/σ_i^2. In this work, the prior mean vector, $\bar{\beta}$, was set to zeros and the prior covariance matrix, Σ_β, was set to zeros on off-diagonal elements and 100 on all diagonal elements (providing essentially no information to the model).

Since the prior is non-informative and the likelihood function only offers bounds on the parameters, the μ values can be drawn from uniform distributions with lower and upper bounds given by $\max_{i \in Q_{s-1}}(U_i)$ and $\min_{i \in Q_s}(U_i)$, where Q_s is the set of all observations such that $y_i = s$.

In the final step, σ_i is drawn from its conditional posterior distribution. For the OP specification, $\sigma_i = \sigma$ and σ^2's prior is inverse gamma, resulting in the following conditional posterior distribution:

Table 1
Maximum injury severity statistics (LTCCS Survey Data).

Outcome	Vehicle-level model		Crash-level model	
	Weighted frequency	Wt.%	Weighted frequency	Wt.%
No injury	695	36.7	n/a	n/a
Possible injury	13	0.7	n/a	n/a
Non-incapacitating injury	728	38.4	501	54.3
Incapacitating injury	380	20.1	343	37.2
Killed	78	4.1	78	8.5

$$p(\sigma^2|U,\beta,\mu,X,Y) \propto \left(\frac{1}{\sigma^2}\right)^{N/2+r+1} \times \exp\left(-\frac{0.5\Sigma_i w_i[U_i - X_i'\beta]^2 + q}{\sigma^2}\right) \tag{13}$$

Thus, σ^2 is distributed inverse gamma with shape and scale parameters of $N/2+r$ and $0.5\sum_i w_i[U_i - X_i'\beta]^2 + q$. Here, r and q were taken as one each (again providing the model very limited prior information).

For the HOP specification, $\sigma_i = \exp(Z_i'\gamma)$ and γ's prior is normal. (Note that in this case, one must draw γ, not σ_i directly.) Since the product of the likelihood and prior does not result in a standard density function, a normal random-walk Metropolis-Hastings (MH) step (see, e.g., Gamerman and Lopes, 2006) is employed to draw γ. The conditional posterior density can be written as follows:

$$p(\gamma|U,\beta,\mu,X,Y) \propto \left[\prod_{i=1}^{N}\left(\frac{1}{\sigma_i}\right)^{w_i}\right] \times \exp\left(-\frac{1}{2}(\Sigma_i \frac{w_i[U_i - X_i'\beta]^2}{\exp[2Z_i'\gamma]} + [\gamma-\bar{\gamma}]'\Sigma_\gamma^{-1}[\gamma-\bar{\gamma}])\right)] \tag{14}$$

Here, the prior mean, $\bar{\gamma}$, was chosen to be zero and the prior covariance matrix, Σ_γ, was set to zeros on the off-diagonal elements and 10 on the diagonal. Like the other priors, this prior offers very little information to the model (essentially allowing the data set [n = 922 and n = 1894 for crash- and vehicle-level models] to determine all estimates).

Of course, the HOP model specification is more flexible than the OP, since it allows the variance term to vary for each observation. The OP is a special case, where all γ_t are effectively zero (other than a constant). Wang and Kockelman (2005) used a similar specification for heteroskedastic ordered logit models of crash outcomes (with mostly light-duty vehicles) and found outcome variance (and thus outcome uncertainty) to rise with speed limit, and vary as a function of vehicle weight and vehicle type (with pickup trucks exhibiting higher uncertainty in all contexts, but weight and other vehicle types having different impacts depending on whether the crash involved one or two vehicles). O'Donnell and Connor (1996) found speed limit to increase variance and thus outcome uncertainty. Unlike these previous studies, this paper uses Bayesian estimation techniques, which offer a distribution of model parameters, rather than single point estimates. This allows the analyst to characterize crash severity outcome uncertainty in a meaningful way.

4. Data description

The primary data used here come from the Large Truck Crash Causation Study Data (LTCCS), collected by the United States' Federal Motor Carrier Safety Administration (FMCSA) and National Highway Traffic Safety Administration (NHTSA). Data were collected on crashes involving at least one truck with gross vehicle weight rating over 10,000 pounds, and an attempt was made during data collection to include only those crashes resulting in at least one injury or fatality (i.e., the three most severe crash types according to the KABCO injury scale[5]). Trained staff from NHTSA's National Automotive Sampling Scheme (NASS) and state truck inspectors collected the LTCCS crash data in 24 data collection sites across 17 states between April 2001 and December 2003. The data collection efforts involved interviews with drivers, passengers, and witnesses.

Two collection sites were selected from each of the nations 12 geographic areas. These areas were defined by four broad regions (northeast, midwest, south, and west), each broken into central city, large county, and county-group categories (as described in the LTCCS Codebook[6]). Analysts estimated a weight for each crash-record to indicate how the data set can be expanded to provide a reasonably representative sample of the nation's injurious large truck crashes.[7] These weights are included in the likelihood functions of the models here.

Two response variables were of interest here, resulting in two different data sets. The first was vehicle-based, and used the *maximum* injury severity suffered by any vehicle occupant. While each vehicle in the dataset was involved in an injurious crash (i.e., the maximum injury severity sustained across all individuals in the crash was injurious or fatal), the maximum vehicle-level injury severity could be coded as any one of the five KABCO severities (including no injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal). However, since there were so few vehicles coded in the "possible injury" category, it was grouped with the "no injury" category for a total of four possible outcomes. The second data set was crash-based, and was used to analyze the *maximum* injury severity suffered by any person involved in the crash. Since, each crash involved at least on injury or fatality, only three possible outcomes could be observed. Explanatory variables include a great variety of driver, environmental, and vehicle attributes, including the attributes of the truck involved. When multiple trucks were involved in a crash, the variables associated with the "largest truck" were used. Largest truck was defined as the truck having the most trailers (and then, in the event of a tie, the longest truck, and then the heaviest truck [according to GVWR]). In the model of occupant injury severity, 1894 observations were used, after removing 8.9% of the records due to missing data. In studying the maximum injury severity, 922 observations were used (after deleting 4.2% of records for which variables were missing). Even after removing records because of missing data, a fairly large number of observations had missing data for the largest trucks length and GVWR (about 22% of crash observations). In order to preserve the sample and because these characteristics were viewed to be potentially important determinants of injury severity outcomes,

[5] These include fatal, incapacitating injury, and non-incapacitating injury crash severities. Other KABCO severity levels are possible injury and no injury.
[6] The Codebook can be found at http://152.122.44.126/ltccs/data/documents/LTCCS_Codebook.pdf.
[7] Only those crashes where at least one injury or fatality occurred were given positive weights.

Table 2
Descriptive statistics (Vehicle-level, $n = 1894$; Crash-level, $n = 922$).

Variable	Vehicle-level		Crash-level		Min.	Max.
	Mean	Std. Dev.	Mean	Std. Dev.		
Crash variables						
Number of involved trucks	n/a	n/a	1.18	0.511	1	5
Number of involved passenger vehicles	1.18	1.138	0.811	0.895	0	28
Number of involved non-motorists	0.011	0.104	0.019	0.137	0	2
Dark indicator	n/a	n/a	0.109	0.312	0	1
Dark, but lighted indicator	0.117	0.321	0.115	0.319	0	1
Dusk/Dawn indicator	0.038	0.192	0.043	0.203	0	1
Wet surface indicator	n/a	n/a	0.159	0.365	0	1
Snowy/Icy surface indicator	n/a	n/a	0.017	0.128	0	1
Snowing indicator	0.009	0.094	n/a	n/a	0	1
Foggy indicator	0.004	0.063	0.004	0.061	0	1
Other weather indicator	0.013	0.113	0.013	0.112	0	1
Overweight indicator (Any truck)	0.071	0.257	0.060	0.237	0	1
Prescription drug indicator (Any Driver)	n/a	n/a	0.457	0.498	0	1
Illegal drug indicator (any driver)	n/a	n/a	0.068	0.252	0	1
Fatigued indicator (any driver)	0.125	0.331	n/a	n/a	0	1
Speeding indicator (any driver)	0.053	0.224	0.104	0.315	0	2
Other aggression indicator (any driver)	0.106	0.308	0.053	0.228	0	2
Total passenger vehicle occupants	n/a	n/a	1.24	1.65	0	40
Total truck occupants	n/a	n/a	1.34	0.698	1	6
Largest truck variables						
Number of truck trailers	0.836	0.480	0.827	0.475	0	2
Single-unit truck indicator	0.188	0.391	0.189	0.391	0	1
Length (ft)	57.1	17.1	57.1	16.7	9.8	105
GVWR (1000 lbs)	103	32.8	103	32.6	10.0	105
Rural non-freeway indicator	n/a	n/a	0.314	0.464	0	1
Curved road indicator	n/a	n/a	0.333	0.471	0	1
Uphill/Downhill grade indicator	n/a	n/a	0.370	0.483	0	1
Road crest indicator	n/a	n/a	0.025	0.156	0	1
Road sag indicator	n/a	n/a	0.005	0.072	0	1
Speed limit (mph)	n/a	n/a	51.7	11.9	15	75
Vehicle/driver variables						
Number of lanes (one directions)	2.93	1.22	n/a	n/a	1	7
Rural non-freeway indicator	0.293	0.455	n/a	n/a	0	1
Rural freeway indicator	0.163	0.369	n/a	n/a	0	1
Urban freeway indicator	0.359	0.480	n/a	n/a	0	1
Uphill grade indicator	0.162	0.368	n/a	n/a	0	1
Illegal drug indicator	0.041	0.199	n/a	n/a	0	1
Vehicle occupants	1.29	0.712	n/a	n/a	1	11
Truck trailers	0.468	0.539	n/a	n/a	0	2
Bus indicator	0.002	0.046	n/a	n/a	0	1
Motorcycle indicator	0.003	0.053	n/a	n/a	0	1
Truck indicator	0.587	0.492	n/a	n/a	0	1

average variable values were used when such data was missing. For single-unit trucks with no trailers, average length and GVWR were 30.5 ft and 50,000 lbs. Average lengths for tractor trailers with 0, 1, and 2 trailers were 25.4, 64.0, and 71.5 ft, respectively, while average GVWRs for such vehicles were 52,900, 116,000, and 133,000 lbs, respectively.

As Table 1 values indicate, in the first data set (vehicle-level), 58.5% of all cases experienced an injury, with fatalities for 4.1% of vehicle observations. In the second data set (crash-level), injuries were observed for 91.5% of the observations, and fatalities for 8.5%.

Table 2 provides summary statistics for all variables used in the study. Variables are partitioned into three groups: crash-level vari-

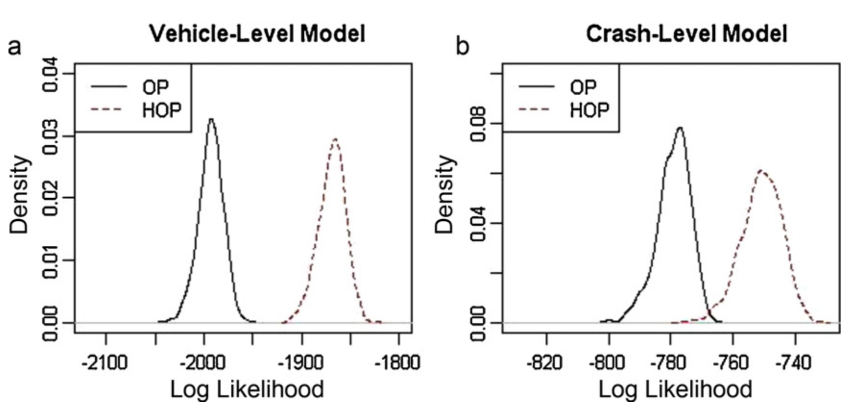

Fig. 1. Log-Likelihood distributions for OP and HOP models of injury severity.

Table 3
Estimation results for vehicle-level OP and HOP models.

Variable	OP		HOP			
	Main effects		Main effects		Variance effects	
	Mean	95% Interval	Mean	95% Interval	Mean	95% Interval
Constant	1.29	(0.986, 1.59)	2.04	(1.78, 2.32)	−1.71	(−2.06, −1.31)
Crash variables						
# Passenger vehicles	−0.276	(−0.314, −0.240)	−0.707	(−0.781, −0.626)	0.393	(0.349, 0.435)
# Non-motorists	−0.892	(−1.34, −0.480)	−3.64	(−10.4, −1.07)	1.50	(0.331, 2.86)
Dark, but lighted	0.201	(0.081, 0.328)	0.124	(0.031, 0.224)	n/a	n/a
Dusk/Dawn	0.115	(−0.093, 0.295)	0.142	(−0.002, 0.265)	−0.343	(−0.627, −0.073)
Snowing	−0.385	(−0.787, −0.007)	−0.094	(−0.417, 0.114)	−0.835	(−1.98, 0.165)
Foggy	0.261	(−0.335, 0.821)	0.260	(0.124, 0.415)	−2.98	(−4.17, −1.87)
Other weather	−0.279	(−0.658, 0.086)	−0.053	(−0.218, 0.112)	−0.273	(−0.771, 0.207)
Overweight (any truck)	−0.181	(−0.355, −0.020)	−0.177	(−0.341, −0.027)	n/a	n/a
Fatigued (any driver)	0.169	(0.052, 0.282)	0.104	(0.014, 0.189)	−0.214	(−0.352, −0.075)
Speeding (any driver)	−0.278	(−0.492, −0.072)	−0.220	(−0.403, −0.028)	−0.055	(−0.308, 0.209)
Other aggression (any driver)	0.397	(0.227, 0.554)	0.210	(0.066, 0.341)	0.101	(−0.091, 0.296)
Largest truck variables						
# Truck trailers	0.199	(0.036, 0.365)	0.219	(0.059, 0.376)	0.167	(−0.082, 0.411)
Single-unit truck	−0.116	(−0.289, 0.065)	−0.153	(−0.292, 0.001)	0.319	(0.065, 0.555)
Length (ft)	−0.005	(−0.009, −0.001)	−0.011	(−0.014, −0.007)	0.011	(0.006, 0.017)
GVWR (10,000 lbs)	−0.010	(−0.030, 0.010)	−0.005	(−0.022, 0.012)	−0.031	(−0.058, −0.005)
Vehicle/driver variables						
Number of lanes (one direction)	−0.041	(−0.074, −0.009)	−0.021	(−0.055, 0.014)	0.024	(−0.021, 0.067)
Rural non-freeway	0.161	(0.041, 0.272)	0.177	(0.081, 0.275)	−0.071	(−0.186, 0.044)
Rural freeway	0.133	(−0.006, 0.261)	0.114	(−0.002, 0.232)	n/a	n/a
Urban freeway	0.104	(−0.006, 0.211)	0.061	(−0.038, 0.165)	n/a	n/a
Uphill grade	0.077	(−0.018, 0.185)	0.089	(0.010, 0.171)	n/a	n/a
Illegal drug	0.253	(0.076, 0.432)	0.102	(−0.041, 0.239)	n/a	n/a
Vehicle occupants	0.040	(−0.009, 0.087)	0.013	(−0.028, 0.053)	n/a	n/a
Truck trailers	−0.178	(−0.305, −0.042)	0.004	(−0.125, 0.140)	−0.272	(−0.444, −0.102)
Bus	−0.444	(−1.14, 0.217)	−0.734	(−1.18, −0.341)	n/a	n/a
Motorcycle	0.489	(−0.114, 1.12)	0.291	(−1.99, 4.08)	1.74	(0.677, 3.11)
Truck	−0.726	(−0.860, −0.592)	−1.13	(−1.28, −1.01)	0.621	(0.437, 0.792)
Structural parameters						
Std. Dev.	0.634	(0.596, 0.677)	n/a	n/a	n/a	n/a
Threshold 3	1.41	(1.36, 1.46)	1.33	(1.29, 1.37)	n/a	n/a
Observations	1894		1894			

Table 4
Average variable effects (per unit change) on outcome severity in the vehicle-level HOP model.

Crash variables	Probability change in outcome			
	Non-injury	Non-incapacitating injury	Incapacitating injury	Fatality
# Passenger vehicles	0.269	−0.144	−0.081	−0.044
# Non-motorists	0.120	−0.215	−0.021	0.116
Dark, but lighted	−0.072	0.045	0.015	0.012
Dusk/Dawn	−0.109	0.138	−0.013	−0.016
Snowing	0.091	−0.029	−0.040	−0.023
Foggy	−0.491	0.561	−0.044	−0.026
Other weather	0.046	−0.008	−0.023	−0.015
Overweight (any truck)	0.101	−0.073	−0.016	−0.011
Fatigued (any driver)	−0.069	0.088	−0.007	−0.012
Speeding (any driver)	0.131	−0.093	−0.023	−0.015
Other aggression	−0.114	0.043	0.032	0.040
Largest truck variables				
# Truck trailers	−0.122	0.043	0.033	0.046
Single-unit truck	0.072	−0.108	0.008	0.029
Length (10 ft)	0.058	−0.058	−0.004	0.004
GVWR (10,000 lbs)	0.033	0.032	−0.026	−0.038
Vehicle/driver variables				
# Lanes (one direction)	0.011	−0.012	0.000	0.001
Rural non-freeway	−0.106	0.083	0.015	0.008
Rural freeway	−0.066	0.041	0.013	0.011
Urban freeway	−0.035	0.024	0.007	0.005
Uphill grade	−0.052	0.033	0.010	0.008
Illegal drug	−0.059	0.036	0.012	0.010
Vehicle occupants	−0.007	0.004	0.002	0.002
Truck trailers	0.000	0.039	−0.020	−0.019
Bus	0.342	−0.281	−0.038	−0.023
Motorcycle	−0.015	−0.307	−0.009	0.331
Truck	0.611	−0.449	−0.113	−0.049

Table 5
Estimation results for crash-level OP and HOP models.

Variable	OP		HOP			
	Main effects		Main effects		Variance effects	
	Mean	95% Interval	Mean	95% Interval	Mean	95% Interval
Constant	−0.223	(−0.837, 0.371)	0.102	(−0.533, 0.763)	−1.42	(−1.99, −0.799)
Crash variables						
# Trucks	−0.112	(−0.337, 0.114)	−0.255	(−0.587, 0.046)	0.429	(0.186, 0.685)
# Passenger vehicles	0.027	(−0.106, 0.165)	0.042	(−0.103, 0.202)	0.181	(0.059, 0.302)
# Non-motorists	1.06	(0.673, 1.51)	1.10	(0.515, 1.71)	0.383	(−0.259, 1.08)
Dark	0.063	(−0.157, 0.281)	−0.094	(−0.507, 0.208)	0.435	(0.085, 0.799)
Dark, but lighted	0.466	(0.236, 0.704)	0.509	(0.310, 0.734)	−0.218	(−0.505, 0.079)
Dusk/Dawn	0.317	(−0.002, 0.638)	0.279	(−0.027, 0.602)	n/a	n/a
Wet surface	−0.147	(−0.369, 0.044)	−0.073	(−0.273, 0.113)	−0.184	(−0.481, 0.115)
Snowy/Icy surface	0.377	(−0.106, 0.845)	−0.100	(−1.71, 1.14)	0.882	(0.055, 1.83)
Foggy	1.18	(0.102, 2.28)	1.08	(0.016, 2.19)	n/a	n/a
Other weather	−0.989	(−2.15, −0.134)	−1.11	(−2.28, −0.184)	n/a	n/a
Overweight (any truck)	−0.384	(−0.742, −0.044)	−0.255	(−0.647, 0.076)	n/a	n/a
Prescription drug (any driver)	0.107	(−0.027, 0.257)	0.048	(−0.091, 0.189)	n/a	n/a
Illegal drug (any driver)	−0.346	(−0.660, −0.059)	−0.660	(−1.360, −0.186)	0.498	(0.045, 0.987)
Speeding (any driver)	0.177	(−0.036, 0.396)	0.059	(−0.157, 0.283)	n/a	n/a
Other aggression (any driver)	−0.535	(−0.939, −0.179)	−0.547	(−0.984, −0.180)	n/a	n/a
Passenger vehicle occupants	0.072	(0.005, 0.139)	0.091	(0.014, 0.171)	n/a	n/a
Truck occupants	0.087	(−0.078, 0.252)	0.137	(−0.026, 0.288)	n/a	n/a
Largest truck variables						
# Truck trailers	0.231	(−0.067, 0.513)	0.273	(−0.023, 0.578)	n/a	n/a
Single-unit truck	−0.208	(−0.540, 0.125)	−0.461	(−0.793, −0.110)	0.584	(0.230, 0.973)
Length (ft)	−0.009	(−0.017, −0.001)	−0.013	(−0.021, −0.005)	0.008	(−0.000, 0.016)
GVWR (10,000 lbs)	−0.022	(−0.060, 0.014)	−0.037	(−0.075, 0.000)	n/a	n/a
Rural non-freeway	0.380	(0.217, 0.554)	0.484	(0.303, 0.668)	−0.241	(−0.474, −0.008)
Curved road	−0.224	(−0.394, −0.063)	−0.222	(−0.404, −0.061)	n/a	n/a
Uphill/downhill grade	0.136	(−0.014, 0.294)	0.160	(0.009, 0.315)	n/a	n/a
Road crest	0.324	(−0.116, 0.724)	0.271	(−0.082, 0.612)	−0.488	(−1.10, 0.105)
Road sag	−1.04	(−3.18, 0.475)	−5.80	(−22.2, 0.111)	0.756	(−0.948, 2.46)
Speed limit (mph)	0.008	(0.001, 0.015)	0.010	(0.003, 0.018)	n/a	n/a
Structural parameter						
Std. Dev.	0.772	(0.684, 0.865)	n/a	n/a	n/a	n/a
Observations	922	922				

Note: No thresholds were estimated here since only three injury categories correspond to crash-level observations (and two thresholds have been fixed, to ensure model identification).

ables, largest truck (in crash) attributes, and vehicle and driver variables. All roadway characteristics (such as grade, curvature, classification, lanes, and speed limit) are shown in the largest truck and vehicle/driver groups, as they pertain to the associated vehicle. The "other weather" indicator variable implies the presence of weather conditions other than rain, snow, or fog (e.g., wind, sleet, hail, and dust). The "other aggression" indicator refers to aggressive driving behavior other than speeding (e.g., tailgating, weaving in and out of traffic, violations of traffic control devices, rapid acceleration, honking horn, flashing lights, obscene gestures, and obstructing the path of others). Finally, uphill and downhill grades are defined as those exceeding 2%.

Data on driver, occupant, truck, and environmental characteristics were examined in a variety of initial model formulations. To arrive at final model specifications, variables that were found to have little practical and/or statistical significance were removed in a sequential variable elimination process. Some variables that were considered intuitively important were retained despite relatively low significance (e.g., the number of trucks and passenger vehicles and dark lighting conditions).

5. Severity model results

The final OP and HOP models (each with the same set of explanatory variables) were compared using total log-likelihood values (across all observations). Since Bayesian estimation output offers a collection of parameter draws from the posterior distribution, each draw is used to compute the likelihood each model would predict the actual severity outcome. Fig. 1a illustrates the distributions of total log-likelihoods for the OP and HOP models of vehicle injury severity, while Fig. 1b illustrates these distributions for the models of crash injury severity.

As shown in Fig. 1a, the HOP's likelihood dominates the OP's 100% of the time. Mean log-likelihoods for the OP and HOP models are −1993 and −1869 with standard deviations of 12.8 and 13.8, respectively. For the crash-level model (shown in Fig. 1b), the HOP's likelihood beats the OP's almost 100% of the time. The mean OP log-likelihood is −779 with a standard deviation of 5.3, while the HOP's mean log-likelihood is −751 with a standard deviation of 6.5. Thus, it seems that heteroskedasticity cannot be neglected for either model, and the HOP model specifications are preferred. The results of these models are discussed below.

5.1. Vehicle-level injury severity models

Table 3 shows all parameter estimates for HOP and OP specifications of maximum injury severity at the vehicle-level. While signs are generally consistent across the two models, one cannot readily appreciate most variables' full effects in the HOP model since most are estimated to affect both the mean and variance of our latent variable. To appreciate the overall impact of each HOP model covariate, Table 4 provides estimates of each variable's effects on crash severity probabilities. These are found by computing the probability of severity outcomes at various levels of each variable (e.g., indicator variables can be 0 or 1, while number of occupants may vary from 1 to 10), and averaging the probability differences that emerge from the unit change differences in the explanatory factors. In other words, these represent average severity outcome probability changes per unit change in the variable.

Rows highlighted in *light* gray in Table 4 indicate variables that reduce the likelihood of fatality, while increasing the likelihood of no injury. Rows highlighted in *dark* gray in the Table indicate variables that increase the chance of fatality, while reducing the probability of no injury. The most practically significant variables are the number of passenger vehicles involved in the crash and an indicator for whether the observed vehicle is a bus or HDT: both increase the likelihood of their occupants departing the crash scene without a KAB injury. This is not a surprising result for the number of passenger vehicles, since each crash involves at least one injury across all involved. If there are more passenger vehicles involved in the crash, exposure risk is spread around, to some extent, leaving any particular vehicles' occupants better off. And larger vehicles, like buses and HDTs, may be safer for their vehicle occupants, by providing a great deal of impact protection from a large mass of yielding steel.

Other highly practically significant variables include the number of non-motorists involved, number of trailers of the largest truck involved, presence of fog, and whether the vehicle is a motorcycle. The number of involved non-motorists increases both the likelihood of fatality within each vehicle involved and the chance of no injury, thanks to greater uncertainty in injury severity. The number of trailers on the largest involved truck reduces the likelihood of no injury, while increasing the probability of each injury type. Of course, a great deal of correlation exists between this variable and the truck-specific variables for the largest involved HDT (i.e., the HDT's single-unit status, length, and GVWR), all of which increase the likelihood of no injury. Thus, drawing firm conclusions based solely on the largest truck's number of trailers may not be wise, and simulations are performed later in the paper to get at a more definitive direction of this effect. The presence of fog greatly reduces the no-injury outcome's likelihood, while greatly increasing the probability of a non-incapacitating injury (and largely maintaining other injury rates). Even though drivers are probably more cautious under such conditions, they simply do not have time to react to their surroundings due to sight distance impairment, which can lead to more injurious crashes. Finally, and not surprisingly, motorcycles fair very poorly in crashes. The probability of fatality for motorcycle riders involved in HDT crashes is estimated to be 30 percentage points higher than that of occupants in other passenger vehicles.

5.2. Crash-level injury severity models

Table 5 provides estimates for the injury severity models at the crash-level. As in the vehicle-level models, one must account for both mean and variance effects to fully appreciate how variables impact outcome probabilities. Table 6 provides estimates of average effects for each explanatory variable in the HOP model (as described earlier). Similar to Table 4, rows highlighted in *light* gray in Table 6 are variables that are estimated to reduce the likelihood of fatality while increasing the likelihood of non-incapacitating injury, while *dark* gray rows are for variables that increase the chance of fatality and reduce the probability of non-incapacitating injury.

All non-bright conditions are estimated to increase the probability of fatality, perhaps because higher speed variations exist at night time, resulting in greater uncertainty in crash outcomes, or because appropriate response under darkness is difficult to come by (see, e.g., Kockelman and Ma, 2007). When the largest truck is maneuvering a curve in the road at the time of the crash or at a sag in the road profile, the likelihood of fatality is predicted to drop. It could be that such roadway geometry increases driver awareness and/or encourages more cautious (e.g., slower) driving. On the other hand, uphill and downhill grades of 2% or more are predicted to have the opposite effect on crash severity. Interestingly and consistent with observations by Khattak et al. (2002) and Wang and Kockelman (2005), wet surface conditions are associated with less severe crashes. However, snowy or icy road conditions and the presence of fog greatly increase the likelihood of fatality. While one might expect drivers to exhibit more caution under such conditions, it could be that drivers simply do not realize how much caution is truly needed since such conditions occur with rarity. Not surprisingly, higher speed limits and any vehicle's speeding just before the crash result in more severe crashes. Somewhat surprisingly, however, when any driver is under the influence of illegal drugs or displaying other aggressive driving behavior (other than speeding), probability of the lowest crash severity is predicted to be higher. In the case of illegal drug use by a driver, the variance component is also predicted to increase, which ends up resulting in a slight increase in the probability of fatality as well.

Table 6
Average variable effects (per unit change) on outcome severity in the crash-level HOP model.

Crash variables	Probability change in outcome		
	Non-incap. injury	Incap. injury	Fatality
# Trucks	0.036	−0.093	0.057
# Passenger vehicles	−0.028	−0.020	0.048
# Non-motorists	−0.219	−0.101	0.320
Dark	0.001	−0.085	0.084
Dark, but lighted	−0.260	0.183	0.077
Dusk/Dawn	−0.129	0.063	0.067
Wet surface	0.051	−0.006	−0.045
Snowy/Icy surface	−0.038	−0.150	0.188
Foggy	−0.392	0.012	0.379
Other weather	0.325	−0.247	−0.078
Overweight (any truck)	0.109	−0.074	−0.035
Prescription drug (any driver)	−0.022	0.013	0.009
Illegal drug (any driver)	0.154	−0.166	0.012
Speeding (any driver)	−0.028	0.015	0.013
Other aggression (any driver)	0.221	−0.156	−0.065
Passenger vehicle occupants	−0.038	0.011	0.027
Truck occupants	−0.061	0.022	0.038
Largest truck variables			
# Truck trailers	−0.123	0.065	0.058
Single-unit truck	0.123	−0.174	0.050
Length (10 ft)	0.052	−0.043	−0.009
GVWR (10,000 lbs)	0.016	−0.009	−0.007
Rural non-freeway	−0.236	0.182	0.054
Curved road	0.100	−0.063	−0.037
Uphill/downhill grade	−0.074	0.042	0.031
Road crest	−0.161	0.187	−0.026
Road sag	0.347	−0.299	−0.048
Speed limit (mph)	−0.046	0.027	0.019

Not surprisingly, the number of trucks, passenger vehicles, and non-motorists involved in the crash all increase the probability of a fatality, as do the number of passenger vehicle and truck occupants. As far as the characteristics of the largest truck involved, the number of trailers is predicted to increase the likelihood of severe injury and fatal crashes, while the total length and GVWR are predicted to reduce those likelihoods. If the largest truck is a single-unit with no trailer, the likelihood of both low severity and fatality rise due to the positive effect of the variable on variance. Of course, these variables exhibit a great deal of correlation, so it would be difficult to make any strong conclusions simply based on isolating just one of these variables. The following presents a more detailed analysis of the largest truck type.

5.3. Crash-level injury severity and costs by largest truck type

To further examine the effect of the largest truck's characteristics on crash injury severity, a simulation experiment was performed. Trucks were classified into five categories: single-unit

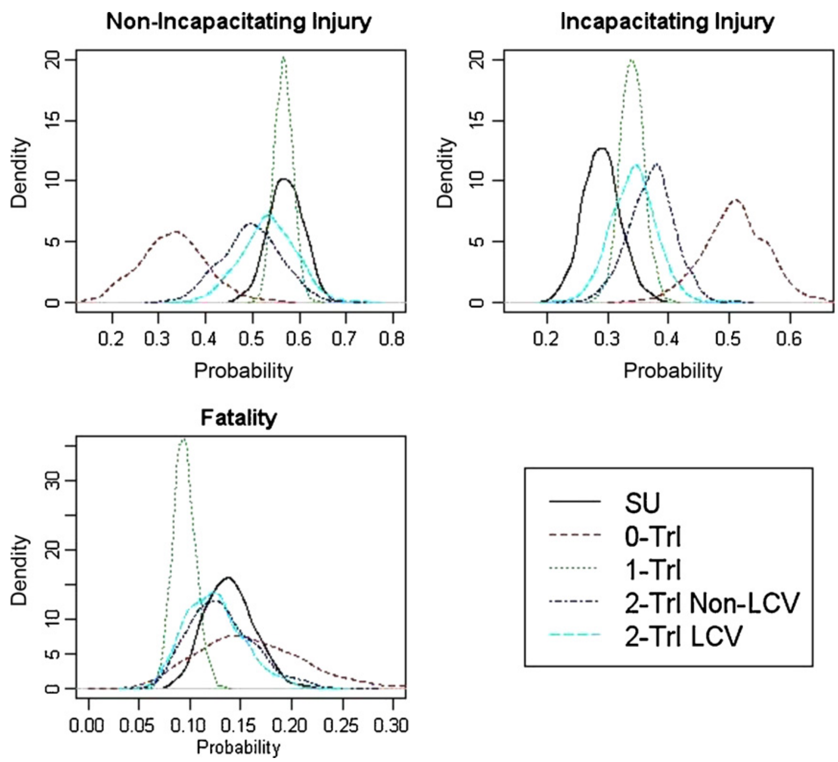

Fig. 2. Distribution of crash severity outcomes by truck type.

with no trailer, 0-trailer tractor, 1-trailer tractor, 2-trailer non-LCV (any 2-trailer HDT with both trailers measuring 28 ft or less), and 2-trailer LCV (2-trailer HDTs where one or both trailers are longer than 28 ft). To perform the simulation, 5000 observations were constructed by drawing randomly from the sample according to observation weights, and largest truck type characteristics were assigned randomly based on the sample collection of each truck type. Thus, for each truck type, 5000 observations were simulated where the non-truck type variables were identical across the truck type simulated data points. Finally, the posterior parameter draws were used to find the distribution of crash severity outcomes according to the type of largest truck involved. Fig. 2 illustrates the findings.

As shown in Fig. 2, once involved in an injurious crash, 1-trailer HDTs are predicted to enjoy the lowest expected crash severity. The 2-trailer LCVs perform nearly the same as 2-trailer non-LCVs and about as well as SU trucks, at least in terms of fatal outcomes. This could be because drivers of such vehicles require more rigorous training and/or they are simply more cautious, so their crashes are less severe. The truck type that performs worst in this case is the 0-trailer tractor. Maybe this is because drivers of such vehicles feel they do not need to drive as carefully when a trailer is not being tow.

In any case, a broader impression of LCV risks requires a look at severity shares for non-injury crash outcomes, which are not recognized in the LTCCS data. Using the U.S. General Estimates System (GES) micro data (which provides crash data for all vehicle involved crash types), from April 2001 to December 2003, estimates of non-injury and injury crash outcomes were found for each truck category. Unfortunately, the GES does not offer truck length data, so crash outcomes for 2-trailer non-LCVs and LCVs are assumed equal here. Based on this information, it appears that 12.4%, 13.1%, 13.9%, and 19.1% of truck crashes result in injury when the largest truck is a single-unit, 0-trailer tractor, 1-trailer tractor, and 2-trailer tractor, with the remaining proportions made up by non-injury and possible injury severity outcomes.

Table 7
Crash cost estimates (in 1000's of 2005 dollars) by injury severity and truck type involved.

Crash severity	Single-unit	0-Trailer	1-Trailer	2- or 3-Trailer
No injury	$13.3	19.1	15.7	24.9
Possible injury	62.4	64.3	91.0	116.9
Non-incapacitating injury	198.2	173.5	171.7	244.1
Incapacitating injury	640.5	381.3	437.8	1,292
Killed	3136	3173	3834	3353

(*Source*: Zaloshnja and Miller, 2007).

Taking it a step further, the GES data set can also be used to obtain estimates of the total number of crashes by largest truck type. Combining this with vehicle-miles-traveled information from the Vehicle Inventory and Use Survey (VIUS) from 2002, it was estimated that single-unit trucks were involved in crashes every 311,000 (311 K) VMT, while 0-trailer, 1-trailer, and 2-trailer tractors were involved in crashes every 371 K, 422 K, and 884 K VMT, respectively. Finally, to obtain crash cost estimates, one can refer to Zaloshnja and Miller (2007) estimates of crash costs by injury severity, as shown in Table 7.[8]

With this new information, it is possible to characterize the distribution of total costs on a crash basis, as well as on a vehicle-miles-traveled basis, as shown in Fig. 3.[9] Fig. 3 illustrates that on

[8] Average fatalities are often valued much higher than \$3M to \$4M in the literature, and Zaloshnja and Miller's (2007) costs may be low. However, the main purpose of introducing these costs is to create a rating mechanism to relate the magnitudes of each crash type. Thus, the key assumption here is that the relative magnitude of costs, by severity level, are reasonable, which they appear to be.

[9] The reason the results are shown as distributions is that the parameters of the severity model are characterized by a posterior distribution rather than as point estimates. Thus, these cost estimate distributions represent uncertainty from the crash severity model.

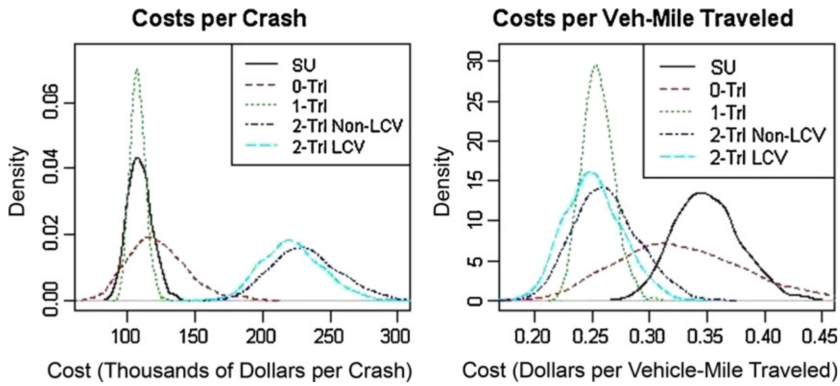

Fig. 3. Per-crash cost estimates, by largest involved-truck type.

a per-crash basis, 2-trailer non-LCVs and LCVs have the highest associated costs by far, with means of about \$232K and \$222K, respectively. When one controls for crash rates by vehicle type, 1- and 2-trailer HDTs have nearly the same average crash costs at \$0.255, \$0.263, and \$0.251 per vehicle-mile for 1-trailer HDTs, 2-trailer non-LCVs, and 2-trailer LCVs, respectively. Single-unit trucks (with no trailer) and 0-trailer tractors are associated with the highest crash costs per VMT, averaging \$0.350 and \$0.330, respectively. Of course, on a per-ton-mile or per-unit-volume basis, LCVs will fare even better, since, presumably, they carry more content.

These results suggest that LCVs are relatively safe. Overall, 2-trailer LCV estimates suggest they may be as safe as their 1-trailer HDT counterparts, on a mileage basis. Of course, on a crash basis, 2-trailer HDTs are less safe than all other truck types, due to their propensity to be involved in more serious crashes – once they are in a crash (which is less often, thanks to a variety of factors).

6. Conclusions

The paper analysis examined the impact of environmental, driver, and vehicle factors on injury severities resulting from large truck crashes by analyzing the U.S.'s recent Large Truck Crash Causation Study (LTCCS) data. Two regression models were developed to study both the maximum injury severity from a crash (over all involved individuals) and the maximum injury severity of occupants of all involved vehicles. Ordered probit (OP) and heteroskedastic ordered probit (HOP) models were examined, and estimation results suggest that the more flexible HOP specifications perform significantly better (thanks to permitting variation unobserved components).

The results of the two crash-conditioned models are generally consistent. For example, the probability of the least severe injury type was greatly increased (given an injurious large truck crash) when the crash occurred at a curve in the roadway, the crash occurred on a roadway sag, any truck involved was overweight, any driver was under the influence of illegal drugs, and/or any driver was exhibiting aggressive driving behavior (other than speeding). The probability of fatality is estimated to rise when non-bright lighting conditions are present, the road surface is snowy or icy, and/or fog is present. In addition, the number of involved passenger vehicle and truck occupants was estimated to increase the likelihood of a fatal outcome. While the number of truck trailers was estimated to increase the likelihood of fatality, total truck length and gross vehicle weight rating (GVWR) attributes were both estimated to reduce fatality likelihood. Taken together, these model estimates suggest 1-trailer trucks are associated with lower severity levels (assuming an injurious crash has occurred) and 0-trailer tractors are associated with the most severe injurious truck crashes, while single-unit trucks and 2-trailer non-LCVs and LCVs perform somewhere in the middle. Of course, one must be careful in drawing conclusions. The estimates here only relate to specific ranges of each variable. If truck length and/or GVWR increase past the levels common in the LTCCS sample, the model's estimates may not be valid.

Various researchers have found that LCVs enjoy lower crash rates than other HDTs (e.g., Montufar et al., 2007 and Woodrooffe, 2001), as confirmed here by combining truck crash data from the GES and truck usage data from the VIUS. Once an analyst conditions on crash occurrence, he/she can evaluate the severity of such crashes, as performed here. While the crash-level model results provided here suggest that LCVs (along with 2-trailer non-LCVs) may be associated with more severe and fatal injury crashes and the costs of those crashes may be highest in comparison to other truck types, such vehicles are associated with lower crash rates (per vehicle-mile traveled). After controlling for exposure, results suggested that LCVs enjoy significantly lower crash costs, per vehicle-mile traveled. This could be a result of any number of factors or combinations of those factors. For instance, LCV drivers are often better-trained and more experienced, many states restrict LCV use when road surfaces are snowy or icy, and LCVs are often restricted to higher-design routes, such as interstates (Abdel-Rahim, 2009 and Regehr, 2009).

Taken all together, the literature and these results suggest that LCVs vehicles deserve closer consideration, particularly if they offer opportunities for lowered transport costs and energy use without negatively impacting pavements, bridges, and other infrastructure elements.

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