ANALYSIS OF LARGE TRUCK CRASH SEVERITY USING HETEROSCEDASTIC ORDERED PROBIT MODELS

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ABSTRACT

Long-combination vehicles have significant potential to increase economic productivity by decreasing the number of truck trips and thus reducing costs. However, size and weight regulations imposed due to 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 heteroscedastic ordered probit models 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 the presence of an LCV can more than compensate for this trend. In addition, injury severity was found to decrease when driving under well lit conditions, on freeways and in the absence of grades.

Keywords: Long-combination vehicles, crash severity, heavy duty truck safety, heteroskedasticity, ordered probit

INTRODUCTION

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 long combination vehicles (LCVs) – defined as large trucks with two or more cargo spaces (and at least one such cargo space longer than 28 feet) – is increasing, both in terms of total vehicle miles travelled (VMT) as well as proportion of vehicles on U.S. highways (Abdel-Rahim et al., 2006). Nevertheless, 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 government before June 1, 1991. Currently, operation of three LCV configurations [1] 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 in on selected routes in six other states (AASHTO, 1995; GAO, 1993).

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 (US GAO, 1992; US DOT, 2000; Craft, 1999).

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

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.

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, Harkey et al., 1996, Hanley et al. 2005, Glaeser et al., 2006, Debauche et al., 2007, Renshaw, 2007, Knight et al., 2008). 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.

Based on the crash histories of multiple-trailer trucks, a USDOT (2000) study 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 (US DOT, 2000). However, LCVs carry more cargo, so their crash-rate per *ton-mile* can be significantly lower. And crash-severity differences can go either way, as discussed below.

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

Truck length is a key variable. Vierth et al. (2008) conducted an analysis of 2003 to 2005 accident data in Sweden to check if the presence of longer trucks results in more overtaking-related crashes and concluded that the increase in accident risk is not statistically significant and is offset by truck-miles reductions (thanks to bigger cargos).

Campbell et al. (1989) surveyed 12 western states where LCV operations were permitted and identified around 550 police-reported crashes involving LCVs. The accident rates were found to be lower than what was expected for combination vehicles, either due to under-reporting or the presence of operational restrictions on LCVs. Using the general estimates system (GES) data from the National Highway Traffic Safety Administration (NHTSA) for the years 1989-1993, Wang et al. (1999) concluded that combination-unit-trucks enjoy significantly lower crash rates as compared to passenger vehicles and single-unit trucks (at rates of 226 combination-unit crashes per 100 million miles traveled, versus 556 for passenger cars, 416 for light-duty trucks, and 289 for single-unit trucks).

Using Alberta, Canada data from 1995 to 1998, Woodrooffe (2001) compared LCV safety to that of other vehicle classes. He determined that the LCVs enjoy the lowest collision rates (per mile-traveled) among all vehicle classes in that region, with fewer than 14 involved LCVs per year. The number of LCV collisions that occurred in rural areas was roughly twice the number of such incidents in Alberta's urban areas. Montufar et al. (2007) conducted a similar study in the Alberta region from 1999 to 2005, to compare and contrast safety performance over the study periods. Their work revealed LCVs to be the safest among all vehicle types, with just 40 collisions for every 100 million miles traveled plus the lowest injury and fatality rates. Driving actions such as improper turning and lane change maneuvers and unsafe roadway conditions such as presence of snow, ice, slush or rain where the major causes of LCV related incidents (Montufar et al., 2007)). Rahim et al. (2006) obtained similar results from analyzing LCV crash data in Idaho, Montana, Oregon and Utah.

Several European countries have been studying the feasibility of using Longer, Heavier Vehicles (LHVs)[2] for freight transport. Debauche et al.'s (2007) safety survey of roughly 100 LHVs for the Dutch Ministry of Transport estimated LHVs to have similar levels of safety when compared to heavy goods vehicles (HGVs)[3] but slightly lower fatal injury crash counts (totaling just 4 to 25 such crashes a year in the Netherlands). Motorists also did not report any decrease in perceived safety level in the presence of a LHV, as opposed to a regular HGV.

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; Zaloshnja et al., 2000), and higher crash costs per incident (Zaloshnja et al., 2000; Wang et al., 1999). Forkenbrock et al. (2003) used multiple classification analysis and automatic interaction detectors for a 1995-1998 Trucks Involved in Fatal Accidents (TIFA) data file, as maintained by the University of Michigan Transportation Research Institute (UMTRI). They concluded that multiple-trailer trucks have a higher likelihood of crash involvement when compared to a single-trailer trucks under difficult driving conditions. Such conditions include darkness, snow on the road, and moderate traffic volumes on reasonably high-speed facilities.

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

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

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

vehicles, and type of impact. Of course, the higher the collision speed, the more severe the crash. Interestingly, as the ratio of vehicle masses increases beyond 50:1 (as is generally the case with LHVs), there was no significant change in incident severity for the passenger vehicle occupants – assuming there are no secondary incidents. 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) has the potential to reduce heavy vehicle crash frequencies by up to 75%, and an even greater percentage for LHVs (Grover et al., 2007; 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 et al. (2008) used the U.S.'s Large Truck Crash Causation Study (LTCCS), which contains information on 963 crashes involving 1,241 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.

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 truck with a gross vehicle weight rating over 10,000 pounds. Such models have been used to analyze crash severity of automobile crashes (Khattak et al., 1998, 2002; Kockelman and Kweon, 2002, 2003; Abdel Aty, 2003; Khattak and Rosa, 2003), with O'Donnell and Connor (1996) and Wang and Kockelman (2005) using heteroscedastic ordered probit and logit models to analyze injury severity. The next section describes the model specification used in this study.

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, as follows:

$$U_i = X_i^{'}\beta + \xi_i \qquad \forall i = 1,..., N \qquad (1)$$

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 ξ_i is an error term representing all unobserved characteristics affecting the crash outcome. In OP models, ξ_i is modeled as a random variable following an i.i.d standard normal distribution for all observations.

The observed variable y_i for the i^{th} 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:

$$y_i = s \quad if \;\; \mu_{s-1} < U_i < \mu_s \qquad \mathrm{s} = 1,.....,\mathrm{S} \qquad (2)$$

Where μ_s denotes the boundary points or thresholds for the latent continuous variable U_i such that $\mu_0 < \mu_1 < \;..\; < \mu_s$ .For the purpose of statistical identification and assuming that the explanatory variables contain a constant term, $\mu_0=-\infty$, $\mu_1=0$ and $\mu_s=\infty$..The probability of observed variable y_i taking an outcome value s is given by:

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

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

In many cases, error terms may not be homoscedastic, and their variance may be parameterized as a function of covariates. In such cases, a heteroscedastic 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 coefficients of either model (OP or HOP) can be estimated by maximizing the likelihood function shown below:

$$L = \prod_{s=1}^{S}\prod_{i=1}^{n}\left(\varphi\left(\frac{\mu_s - X_i'\beta}{\sigma_i}\right) - \varphi\left(\frac{\mu_{s-1} - X_i'\beta}{\sigma_i}\right)\right)^{w_{is}} \tag{6}$$

where w_{is} represents the population expansion factor (or crash-record weight, as provided by the LTCCS data) for the i^{th} observation having an outcome s. All $\sigma_i = 1$ in the OP case.

This paper looks at factors affecting the maximum injury severity level associated with a crash and the injury severity of all affected individuals. For both the models the Maximum Abbreviated Injury Scale (MAIS) is used to describe the outcomes.

$y_i = 0$ (no injury) if $U_i \le \mu_1 = 0$

$y_i = 1$ (no visible injury, only pain reported) if $0 \le U_i \le \mu_2$

$y_i = 2$ (non-incapacitating injury) if $\mu_2 \le U_i \le \mu_3$

$y_i = 3$ (incapacitating injury) if $\mu_3 \le U_i \le \mu_4$

$y_i = 4$ (death) if $U_i \ge \mu_4$ (7)

In the standard OP model positive coefficient estimates (β) indicate that increases in the associated explanatory variable increase the likelihood of a fatal outcome (and reduce the likelihood of a no-injury outcomes), whereas negative coefficients suggest the reverse. The marginal effect of each variable (x_t) on individual probabilities of all five outcomes can be calculated as follows:

$$\frac{\partial P(y=s)}{\partial x_t} = -\left[f\left(\mu_s - \overline{X}\beta\right) - f\left(\mu_{s-1} - \overline{X}\beta\right)\right]\beta_t \tag{8}$$

where $\overline{X}$ is the population-weighted average vector of all explanatory variables, f is the probability density function for the standard normal distribution, and β_t is the coefficient interacted with variable x_i. For indicator variables (x_t = [0,1]), marginal affect is the difference in probabilities at x_t = 1 versus x_t = 0, and all other variables fixed at their average values.

In the case of an HOP model, variables can affect the spread of the latent variable U_i, not just its location, so positive versus negative signs on coefficients (β) are not as telling, in terms of the likelihood of fatal versus no-injury outcomes. One must evaluate the standard deviation implied by changes in x_t before characterizing the overall impact. Marginal effects can be estimated as follows:

$$\begin{aligned}\frac{\partial P(y=s)}{\partial x_t} &= \left[f\left(\frac{\mu_s - \overline{X}\beta}{\overline{\sigma}}\right) - f\left(\frac{\mu_{s-1} - \overline{X}\beta}{\overline{\sigma}}\right)\right]\frac{\beta_t}{\overline{\sigma}}(\gamma_t \overline{x}_t - 1) \\ &\quad - \left[\mu_s f\left(\frac{\mu_s - \overline{X}\beta}{\overline{\sigma}}\right) - \mu_{s-1} f\left(\frac{\mu_{s-1} - \overline{X}\beta}{\overline{\sigma}}\right)\right]\frac{\gamma_t}{\overline{\sigma}}\end{aligned} \qquad (9)$$

In the above expression $\overline{\sigma}$ is the weighted average of variance and γ_t represents the coefficients of variable x_t in explaining the variance (as per Eq. 4). If the variable x_t is not a covariate in explaining response variance, then the marginal effect expression reduces to the following:

$$\frac{\partial P(y=s)}{\partial x_t} = \left[f\left(\frac{\mu_s - \overline{X}\beta}{\overline{\sigma}}\right) - f\left(\frac{\mu_{s-1} - \overline{X}\beta}{\overline{\sigma}}\right)\right]\frac{\beta_t}{\overline{\sigma}} \qquad (10)$$

The effect of binary indicator variables is calculated the same way as in OP, by evaluating simple differences in probabilities.

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 heteroscedastic 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 Conner (1996) found speed limit to increase variance and thus outcome uncertainty.

DATA DESCRIPTION

The 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). These include crashes involving at least one truck with a gross vehicle weight rating over 10,000 pounds. 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 2001 and 2003. The data collection efforts involved interviews with drivers, passengers and witnesses.

Two collection sites were selected from each of the nation's 12 geographic areas. These areas were defined by four broad regions (northeast, midwest, south and west), each broken into three central city, large county and county-group categories (as described in the LTCCS Codebook[4]). 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 large-truck crashes. These weights are included in the likelihood functions (Eq. 6) maximized here.

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[4] The Codebook can be found at http://152.122.44.126/ltccs/data/documents/LTCCS_Codebook.pdf.

Two response variables were of interest here, resulting in two different data sets. The first was crash-based, and used to analyze the *maximum* injury severity suffered by any person involved in that crash. The second was person-based and used to study the injury severity of each involved person. Explanatory variables include a great variety of driver, environmental, and vehicle attributes. When multiple trucks were involved in a crash, the variables associated with the "largest truck" and its driver 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 studying the maximum injury severity, 785 observations were used (after deleting 26% records for which variables were missing). In the model of occupant injury severity, 2236 observations were used, after removing 26% of the records due to missing data.

As Table 1 values indicate, in the first data set (maximum injury in a crash), 86% of all cases experienced an injury, with fatalities for 19.2 % of records. In the second data set, injuries were observed for 60.7% of the observations, and fatalities for 8.6 % fatalities (unweighted proportions). Tables 2 and 3 provide summary statistics for all variables used in the study.

Data on driver, occupant, truck and environmental characteristics were examined in a variety of initial model formulations. Interesting variables which had a significant number of missing values include truck weight and speed (preceding crash). Removing such records (up to 50% of the data set) generally lead to weaker model specifications, where a number of other variables became statistically insignificant (due to reduced sample size). Other variables considered, but found to be statistically insignificant, include truck length, driver height and weight, driver familiarity with the road and truck being driven, work-pressure related variables, existence of sight restrictions and blind spots, and presence of a horizontal curve (at or preceding the crash location). Note that the effect of truck length and weight can be correlated, and these effects were to some extent captured by the number of trailer variables.

ANALYSIS OF RESULTS

The final OP and HOP models (each with same set of explanatory variables were compared using Likelihood Ratio (LR) tests (Green, 2002), to ascertain whether the HOP's added flexibility was not useful to prediction, as follows:

$$LR_{MaxInj} = -2(\ln L_{OP} - \ln L_{HOP}) = -2(-907.542 - (-891.23)) = 32.62 > \chi_8^2$$

$$LR_{MaxInj} = -2(\ln L_{OP} - \ln L_{HOP}) = -2(-3173.64 - (-3196.73)) = 46.18 > \chi_8^2$$

Thus, the null hypothesis ($\gamma = 0$) can be rejected at a significance level of 0.05 for both the maximum injury severity model and the injury severity model. The effect of heteroscedasticity cannot be neglected, and the HOP model specifications are preferred here. Their results are discussed at length below.

Maximum Injury Severity Model

Table 4 shows all parameter estimates for both the HOP and OP models of maximum injury severity. The signs on coefficients are same for both sets of explanatory variables, but magnitudes do differ. In the HOP model almost all variables enjoy higher statistical significance than their OP-model counterparts.

Higher truck counts, and more lanes are estimated to shift the latent injury response variable (U_i) to lower severity, and both these variables are associated with higher response variance. While number of trailers are associated with more severe latent response mean value, it brings down outcome variance. Non-bright conditions are estimated to raise both severity and variance, while freeway crash location is estimated to reduce both. One possible explanation for such results is that higher speed variations emerge at nighttime and along freeways, resulting in greater uncertainty in crash outcomes (e.g., Kockelman and Ma, 2004). Interestingly, wet conditions are associated with less severe crashes and sag curves with more severe crashes, with neither exhibiting a statistically significant effect on response variance. Wang and Kockelman (2005) and Khattak et al. (2002) have made similar observations for the wetness condition.

To appreciate the magnitude of effect of each of these variables, as well as the net result of all variables having effects on both mean and variance, one can turn to Eq. 9's estimates. Table 5 provides estimates of the marginal effect of all explanatory variables. According to Table 5 values, the necessity of speeding (SpeedingValid=1) and bright light crash conditions appear to be the most practically significant, and severe-injury reducing, variables (with fatality probability reductions of 94% and 151%, respectively). Others have found such results for lighting (see, e.g., Khattak et al., 2002; and Abdel-Aty et al., 2003).

As shown, incapacitating injury and fatal outcomes are less likely with more involved trucks perhaps due to better balance in vehicles' sizes and weights. The risk of severe injury and fatality rise with the number of trailers on the largest truck, yet such probabilities fall (by 18% and 46%, respectively) when the largest truck is an LCV. The LCV indicator appears to be so helpful, in fact, that its fatality-reducing effect is only offset by having at least two trailers on the truck. This may be due to LCVs traveling at more regulated speeds, on higher-design and pre-approved facilities, with better-trained drivers than the average HDT.

As one might expect, the likelihoods of incapacitating injury and fatality rise rather significantly (by 20% and 82%, respectively) when drugs is involved (i.e., at least one of the involved persons had tested positive). The likelihood of an incapacitating injury was also estimated to rise significantly (by 48%) when the driver of the largest truck reported being emotionally stressed (due to family, health or other reasons).

The likelihood of fatalities is estimated to increase by 52% when the road is an undivided, two-way facility. Similar observations have been made in other crash studies (Wang and Kockelman, 2005) for crashes of all types, where the presence of barriers decreased injury severity. The probability of fatality also is estimated to fall as the number of lanes increase (28%) and when the roadway is an urban or rural freeway (57% and 53%, respectively). This is probably more lanes and freeway status accompany higher design standards (including wider clear zones, better pavements, and the like).

Finally, the presence of sag or a crest curve is estimated to increase the likelihood of a fatality by 54%. This may be because sight distances are reduced on vertical curves, and HDTs and LCVs have difficulty keeping speeds in synch with nearby vehicles. Similar results have been observed in Wang and Kockelman (2005) and Dissanayake and Lu (2002), where grades were found to increase injury severity in both one- and two-vehicle crashes.

Injury Severity Model

Table 6 provides estimates for the injury severity model for all involved persons, with marginal effects in Table 7. As in the maximum injury severity model, the number of involved HDTs is predicted to increase injury severity, while the likelihood of fatality falls with an increase in number of lanes and when the facility is a freeway. However, the variance of the outcome increases with number of lanes and decreases if it is a freeway – in contrast to the effects observed in the maximum injury severity model results. LCV involvement was found to increase the probability of fatality yet reduce outcome variance. This also stands in contrast to effects anticipated in the maximum injury severity model.

Similar to the maximum injury severity model, the likelihood of fatality increases when the crash occurs at a crest or sag, or lighting is inadequate. As shown in Table 7, the presence of a sag or crest is estimated to decrease the probability of no injury by 0.13 (or 32%) and increase the probability of incapacitating injuries by 0.10 (or 48%) and fatality by 0.04 (a striking 132%). The probabilities of fatal injury and incapacitating injury are estimated to rise by 0.01 (or 80%) and 0.14 (or 20%), respectively, when there is inadequate lighting.

In terms of new variables found in this form of the model (versus a focus on maximum injury sustained), there are several to highlight. For example, the likelihood of incapacitating and fatal injuries falls significantly (by 32%) with use of ITS equipment such as headway detection, side object detection and rollover warning. This is consistent with results by those who recommend using technology to increase truck safety (e.g., Knight et al, 2008; and Debauche et al., 2007). However, an increase in ITS equipment use is estimated to increase outcome variance, perhaps because much of the technology goes unexploited?

Crash-involved males also enjoy lower likelihoods of injury and death, as compared to women (e.g., 66% lower likelihood of no injury), and as confirmed in various other studies (e.g., Wang and Kockelman, 2005; Farmer et al., 1997; and Bedard et al., 2002). However, a male’s outcome tends to be more variable. Interestingly, the presence of flow restrictions (such as work zones, prior crash conditions, and existing congestion) was found to decrease risk of fatality by 51%, perhaps due to greater driver care and lower speeds (and more synchronized speeds, across vehicles) in such sections. Finally, wet conditions are associated with less severe crashes and do not seem to have a statistically significant effect on response variance. Wang and Kockelman (2005) and Khattak et al. (2002) have made similar observations for the wetness condition.

CONCLUSIONS

The paper analysis examines the impact of environmental, driver and truck related factors on injury severities resulting from large truck crashes by analyzing the Large Truck Crash Causation Study Data (LTCCS). Two statistical regression models were developed studying both the maximum injury severity from a crash and the injury severity of all affected persons. Ordered probit (OP) and heteroscedastic ordered probit (HOP) were examined, with likelihood ratio test results favoring the HOP specifications.

The results of the two models were often at odds. For example, the likelihood of a crash’s maximum sustained injury being a fatality was estimated to fall with the number of involved trucks and with an LCV in the mix, while injury severity of any involved person was found to increase. These probabilities were estimated to rise and fall with number of trailers (on longest/largest crash-involved truck). A driver’s emotional state and presence of drugs increased risks. Presence of a median or other barrier (to separate opposing flows) and freeway designation reduced injury risks, while the inadequate lighting and the presence of vertical curves increased these. Flow restrictions and wet driving conditions also were found to reduce injury severity.

Various researchers have found that LCVs enjoy lower crash rates than other HDTs (e.g., Woodrooffe,, 2001; and Montufar, 2007). Once one conditions on crash likelihood, one can evaluate the severity of such crashes, as done here. While the maximum-injury model results provided here suggest that LCVs are not associated with more severe and fatal injury crashes, such vehicles are associated with more severe injuries overall (once a crash has occurred), across all crash involved persons, ceteris paribus.

In addition, injury severity is found to fall under well lighted conditions, on limited grades, and along well designed highways (such as freeways). Such design conditions as well as a number of other attributes are estimated to more than offset any LCV-associated increases in outcome severity, once a crash has occurred. 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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LIST OF TABLES

TABLE 1: Injury Severity

Outcome	y	Max. Injury Severity Model		Injury Severity Model	
		Frequency	Percentage	Frequency	Percentage
No Injury	0	10	1.3%	917	39.3%
Injury - Not Visible	1	100	12.7	367	15.7
Injury – Non-InCapacitating	2	262	33.4	490	21
Injury - Incapacitating	3	262	33.4	360	15.4
Death	4	151	19.2	202	8.6

TABLE 2: Descriptive Statistics of Variables Used in Maximum Injury Severity Model

Variable Name	Variable Description	Min	Max	Mean	Std Dev
TruckCount	Number of trucks involved in Crash	1	5	1.16561	0.495
iCrashDrug	Indicator variable to denote involvement of drugs	0	1	0.61656	0.48653
NumTrailer	Number of trailers of the largest truck	0	2	0.81146	0.515
iLCV	Indicator variable to denote if the largest truck is an LCV where an LCV is defined as a truck with two or more trailers and longer than 25 m	0	1	0.02166	0.14565
iEmotional	Indicator variable to denote if the truck driver was emotionally distressed	0	1	0.01274	0.11222
iUnDividedTwoWay	Indicator variable to denote if the crash occurred on an undivided two way	0	1	0.4051	0.49122
iNumLanes	Number of lanes of the facility	1	7	3.1172	1.31185
iNotBrightLight	Indicator variable to denote if the crash did not occur in bright daylight	0	1	0.26242	0.44023
iRuralFreeway	Indicator variable for rural freeway	0	1	0.13248	0.33923
iUrbanFreeway	Indicator variable for urban freeway	0	1	0.42803	0.49511
SpeedingValid	Indicator variable to denote if the driver had a valid reason for speeding	0	1	0.20764	0.40588
iSag	Indicator variable to denote if the crash occurred on a sag curve	0	1	0.02293	0.14978

TABLE 3: Descriptive Statistics of Variables Used in Injury Severity Model

Variable Name	Variable Description	Min	Max	Mean	Std Dev
iMale	Indicator for male driver	0	1	0.75257	0.495
TruckCount	Number of trucks involved in crash	1	5	1.22517	0.48653
NumTrailer	Number of trailers of the largest truck	0	2	0.81293	0.14565
iLCV	Indicator variable to denote if the largest truck is an LCV where an LCV is defined as a truck with two or more trailers and longer than 25 m	0	1	0.01969	0.11222
NumITSCount	Number of ITS equipments on the largest truck	0	3	0.03682	0.49122
iFlowRestriction	Indicator variable to denote if there was any flow restriction on the facility	0	1	0.18193	1.31185
iNumLanes	Number of lanes of the facility	1	6	3.24015	0.44023
iNotBrightLight	Indicator variable to denote the accident did not occur in daylight	0	1	0.25043	0.33923
iFreeway	Indicator variable for freeway	0	1	0.58776	0.49511
iWet	Indicator variable to denote wet conditions	0	1	0.16182	0.40588
iSag	Indicator variable to denote sag or crest curve	0	1	0.02183	0.14978

TABLE 4: Results of the Maximum Injury Severity Model

	HOP		OP	
Variable	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**
Constant	2.19448		2.33662	
TruckCount	-0.19441	1.17	-0.17553	1.17
iCrashDrug	0.25557	.6166	0.27937	.6166
NumTrailer	0.24033	.8115	0.27015	.8115
iLCV	-0.25108	.0217	-0.3532	.0217
iEmotional	0.31632	.0127	0.41878	.0127
iUnDividedTwoWay	0.18168	.4051	0.16662	.4051
iNumLanes	-0.03843	3.1172	-0.04112	3.1172
iNotBrightLight	0.18454	.2624	0.19944	.2624
iRuralFreeway	-0.35049	.1325	-0.32095	.1325
iUrbanFreeway	-0.50801	.4280	-0.56743	.4280
SpeedingValid	-0.48772	.2076	-0.5175	.2076
iSag	0.69812	.0229	0.84766	.0229
Variance				
TruckCount	0.07335	1.17		
NumTrailer	-0.07064	.8115		
iEmotional	-0.41861	.0127		
NumLanes	-0.04419	3.1172		
iNotBrightLight	0.16051	.2624		
iUrbanFreeway	0.114	.4280		
SpeedingValid	-0.29315	.2076		
ISag	-0.45181	.0229		
Thresholds				
μ_0	0	-	0	-
$\mu 1$	0.95969	13.95	1.00556	17.92
$\mu 2$	1.91485	29.643	2.08192	40.21
$\mu 3$	3.52671	31.901	3.8323	49.24
Log L	-891.23		-907.54	
Num Observation	785			

TABLE 5: Marginal Effects for HOP Model of Maximum Injury Severity

Variable	Difference in Probabilities				
	p(y=0)	p(y=1)	p(y=2)	p(y=3)	p(y=4)
TruckCount	0.00742	0.01793	-0.009	-0.02458	0.00823
iCrashDrug	-0.01158	-0.05099	-0.04916	0.08699	0.02473
NumTrailer	-0.01061	-0.03337	-0.00806	0.05154	0.00051
iLCV	0.01397	0.05408	0.04151	-0.08921	-0.02035
iEmotional	-0.01558	-0.10557	-0.08618	0.23198	-0.02465
iUnDividedTwoWay	-0.00732	-0.03468	-0.03732	0.06018	0.01914
NumLanes	0.00183	0.01851	0.03587	-0.0359	-0.0203
iNotBrightLight	0.00604	-0.00954	-0.06739	0.02097	0.04992
iRuralFreeway	0.02007	0.07579	0.05652	-0.12426	-0.02812
iUrbanFreeway	0.03584	0.11489	0.06874	-0.18684	-0.03264
SpeedingValid	-0.00204	0.07005	0.17322	-0.17849	-0.06274
iSag	-0.01661	-0.12055	-0.24192	0.35491	0.02417

TABLE 6: Results of the Injury Severity Model

	HOP		**OP**	
Variable	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**
Constant	1.47662	25.4706	0.95577	10.5266
iMale	-0.53246	-21.3743	-0.33452	-6.42869
TruckCount	-0.24324	-9.46928	-0.12576	-3.24762
NumTrailer	0.12015	4.18252	0.06688	1.38027
iLCV1	0.38336	3.80239	0.21414	1.26683
NumITSCount	-0.94744	-8.09042	-0.44407	-2.51474
iFlowRestriction	-0.57633	-17.4541	-0.40862	-6.18125
NumLanes	-0.12342	-11.4386	-0.073	-3.85189
iNotBrightLight	0.2125	6.61476	0.16286	3.0109
iFreeway	-0.11435	-4.58303	-0.09849	-2.00747
iWet	-0.307	-11.6764	-0.22048	-3.76836
iSag	0.52297	10.7601	0.35845	2.54166
Variance				
iMale	0.27108	6.06745		
TruckCount	0.08873	2.36851		
iLCV1	-0.14967	-1.2351		
NumITSCount	0.24303	1.31963		
NumLanes	0.02415	1.30231		
iNotBrightLight	0.06425	1.23372		
iFreeway	-0.11012	-2.37037		
Thresholds				
μ_0	0	-	0	-
μ1	0.45006	13.52	0.31678	18.89
μ2	1.27388	16.94	0.90564	35.59
μ3	2.98778	19.13	2.14353	42.45
Log L	-3173.64		-3196.73	
Num Observation	2236			

TABLE 7: Marginal Effects of HOP Model for Injury Severity

Variable	Difference in Probabilities				
	p(y=0)	p(y=1)	p(y=2)	p(y=3)	p(y=4)
iMale	0.18348	-0.0245	-0.08274	-0.08375	0.00751
TruckCount	0.05978	-0.01028	-0.02652	-0.0252	0.00222
NumTrailer	-0.13473	-0.10958	0.02856	0.0857	0.02249
iLCV1	-0.12809	0.01109	0.05	0.0666	0.0004
NumITSCount	0.25889	-0.02674	-0.09281	-0.12955	-0.00979
iFlowRestriction	0.16072	-0.00411	-0.05305	-0.08985	-0.01371
NumLanes	0.03137	-0.00257	-0.01042	-0.01646	-0.00192
iNotBrightLight	-0.05129	-0.00928	-0.00054	0.04146	0.01965
iFreeway	0.02219	0.0141	0.01264	-0.02932	-0.01961
iWet	0.08553	-0.00072	-0.03271	-0.04668	-0.00543
iSag	-0.13624	-0.0099	0.00517	0.10097	0.04