Modeling Injury Severity of Multiple Occupants of Vehicles

Copula-Based Multivariate Approach

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Research to date on crash injury severity has focused on the driver of the vehicle or the most severely injured occupant. Though useful, these studies have not provided injury profiles of all occupants in crash-involved vehicles. This lack of a comprehensive picture has limited the ability to devise measures that enhance the safety and reduce the severity of the injury sustained by all vehicular occupants. Moreover, such studies ignore the possible presence of correlated, unobserved factors that may simultaneously affect the injury severity levels of multiple occupants. This paper aims to fill the gap by presenting a simultaneous model of injury severity to apply to crashes that involve any number of occupants. A copula-based methodology, which could be used to estimate such complex model systems, was applied to a data set of crashes drawn from the 2007 General Estimates System in the United States. The model estimation results provide strong evidence of the presence of correlated unobserved factors that affect injury severity levels of vehicle occupants. The correlation exhibited heterogeneity across vehicle types, with a greater level of interoccupant dependency in heavy SUVs and pickup trucks. The study also sheds light on how numerous exogenous factors—including occupant, vehicle, and crash characteristics; environmental factors; and roadway attributes—affect the injury severity levels of occupants in different seat positions. The findings confirm that rear-seat passengers are less vulnerable to severe injuries than front-row passengers and point to the need to enhance vehicular design features that promote front-row occupant safety.

The *Global Status Report on Road Safety* published recently by the World Health Organization (WHO) paints a grim picture of safety statistics on the world's highways (*1*). On the basis of a 2008 survey of 178 countries, the report notes that nearly 1.3 million people are killed and 20 to 50 million people are injured every year in roadway crashes around the globe. The annual cost of highway crashes to governments worldwide is estimated to be $518 billion U.S. dollars. In the United States, about 40,000 fatalities and 2.3 million injuries occur on the nation's highways every year (*2*). Although WHO notes that traffic rule enforcement, strict licensing standards, enhanced driver training, and community safety education campaigns would improve roadway safety, it also identifies a need for greater understanding of crash causation, injury severity, and risky road-use behavior as one of the keys to reduce roadway fatalities and injuries. This paper directly addresses this need by identifying both observed and unobserved factors that contribute to the injury severity of multiple occupants in a vehicle, a topic that has received little attention in the literature.

Multiple occupants in a vehicular crash may experience varied levels of injury as the result of a wide array of factors. Some factors may be observed (and therefore measured and reported in crash data sets). These may include seat belt use, alcohol use, vehicle type, and occupant position. Other factors, however, may go unobserved (and therefore unmeasured and unreported in crash data sets). These factors may include vehicle condition and maintenance record, vehicle speed at the time of crash, the condition and effectiveness of the vehicle safety equipment, and the mental and physical state of the individual occupants. Given the potentially wide array of factors, both observed and unobserved, that may affect injury severity and given that injury severity may vary across occupants in a vehicle, the field would benefit from a study that modeled injury severity of multiple vehicle occupants while it accounted for common observed and unobserved factors that might contribute to injury severity levels experienced by different occupants. This paper aims to present such a model system so that safety counter-measures can be devised to reduce injury severity levels for all vehicle occupants simultaneously.

The study of injury severity that results from crashes has been of much interest. A large body of literature reports on efforts to model injury severity, usually by adopting some form of ordered-response model specification. Typically, these studies have examined the crash injury severity of the driver or of the most severely injured vehicle occupant (*3–6*). Little simultaneous modeling has been done, however, of the injury severity of multiple occupants in a crash vehicle. Studies that have attempted to model the injury severity of two vehicle occupants (usually the driver and the most severely injured passenger) include those by Hutchinson (*7*) and Yamamoto and Shankar (*8*). In both studies, a bivariate probit model specification was adopted. The bivariate probit model specification incorporates the ability to account for the presence of common unobserved factors that influenced injury severity across two vehicle occupants. Modeling injury severity simultaneously for more than two vehicle occupants presents a methodological challenge, however, because of the computational complexity associated with the specification, identification, and estimation of a multivariate probit model with more than two dimensions. This paper overcomes this challenge by presenting a simple and practical modeling approach and specification that accommodates the simultaneous analysis of injury severity of any number of vehicle occupants by seat position. The focus of this paper on injury

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severity as related to seat position is motivated by the considerable attention that has been devoted to this issue in the literature. Numerous studies have examined the injury severity levels sustained by children seated in different positions in vehicles (*9–12*). Virtually all of them have reported that children seated in the front are more likely to sustain fatal or severe injuries than children seated in the rear.

Analysis of the severity of injuries sustained by multiple occupants in a vehicle has been challenged by the difficulties associated with modeling such phenomena in a simultaneous (or joint) equations' framework. Several studies have employed descriptive statistical analysis techniques, logistic regression approaches, or ordered-response structures to model the severity of occupant injury. They have done so with explicit consideration of seat position but as an explanatory variable. Evans and Frick (*13*), Smith and Cummings (*14, 15*), Wang and Kockelman (*16*), Claret et al. (*17*), and Mayrose and Priya (*18*) are examples. All of these studies reported that passengers seated in the rear seat sustained less severe injuries than those seated in the front; those seated in the rear-middle position generally sustained the least severe injuries among all occupants. O'Donnell and Connor (*3*) undertook a comprehensive analysis of occupant injury severity by using ordered logit and probit models and reported that the driver's seat was the safest of all.

Although previous studies have shed light on the influence of seat position on occupant injury severity, little joint modeling has been done that accounts for both observed and unobserved factors that have a simultaneous impact on multiple occupant injury severity. Hutchinson (*7*) and Yamamoto and Shankar (*8*) created an impetus for such modeling. Yet, as already mentioned, further work has been hampered by the methodological challenges associated with specifying, identifying, and estimating simultaneous equation models. This paper aims to make a substantive contribution to the field by presenting a copula-based methodology that can be applied to estimate models of injury severity experienced by any number of occupants in a vehicle simultaneously. The methodology was applied to a data set of crashes drawn from the 2007 General Estimates System (GES) in the United States from jurisdictions across the country.

This paper presents the methodology, describes the data set, provides the model estimation and validation results, and offers some concluding thoughts.

METHODOLOGY

Consistent with the literature on injury severity analysis, this paper adopts an ordered-response modeling approach with the implicit assumption of an underlying, continuous, latent variable whose horizontal partitioning maps into the observed injury severity level. Of explicit consideration was the potential interdependence of injury severity among different occupants of the same vehicle as a result of both observed and unobserved exogenous factors. If no common unobserved factors affect injury severity across multiple vehicle occupants, then the independent ordered-response models of injury severity can be estimated separately for each vehicle occupant. If common unobserved factors do exist, however, a simultaneous ordered-response model of vehicle occupant injury severity must be specified and estimated that accommodates error correlations needs. Common unobserved factors may include such variables as vehicle speed at the time of crash, vehicle condition and maintenance record, condition of vehicle safety equipment, vehicle safety features, and the state of passengers before the crash. The simultaneous equations modeling of occupant injury severity is a classic case of analyzing clusters of dependent random variables, which has widely been considered in transportation and other fields (*19–21*). Such studies, however, placed restrictions a priori on the dependency surface that characterized the relationship between the dependent random variables (mostly through what amounted to a symmetric, multivariate, normal dependency surface). Dependence among the injury propensities of vehicle occupants may be asymmetric, however (for instance, vehicle occupants that had a simultaneously high propensity for high injury severity levels but not necessarily a propensity for simultaneously low injury severity levels). Even if symmetric, the specific parametric functional form of the dependency may take on one of several profiles. The approach described here enabled a test of the appropriateness of different parametric dependency surfaces to select the one that empirically fit the data best.

A copula-based approach was adopted to accommodate the dependence in injury severity propensity among multiple vehicle occupants. In particular, the Archimedean group of copulas was used to implement a computationally feasible maximum likelihood procedure for parameter estimation. The copula-based approach offers the ability to formulate a closed-form likelihood function that eliminates the need to adopt the more computationally intensive, simulation-based procedures for parameter estimation. Other advantages associated with the Archimedean group of copulas for model estimation are as follows:

- They can be used to obtain the joint multivariate cumulative distribution function of any number of individuals belonging to a cluster. Further, these copulas retain the same form regardless of cluster size, thus accommodating clusters of varying sizes in a straightforward manner.
- They allow a variety of radially symmetric and asymmetric joint distributions to be tested, as well the assumption of within-cluster independence.
- The approach enables the specification of a variety of parametric marginal distributions for individual members in a cluster and preserves these marginal distributions when the joint probability distribution of the cluster is developed. Further, the approach separates the marginal distributions from the dependence structure so that the dependence structure is entirely unaffected by the marginal distributions assumed.
- The approach allows the level of dependence within a cluster to vary on the basis of cluster type. For example, the level of dependence of injury severity across vehicle occupants may be influenced by vehicle type and other vehicle characteristics. In fact, it is possible to allow the dependency structure to be different across cluster types (say, vehicle types) by using different copulas for different cluster types.

Copula-Based Approaches

A copula is a device or function that generates a stochastic dependence relationship (i.e., a multivariate distribution) among random variables with prespecified marginal distributions. Bhat and Eluru (*22*) and Trivedi and Zimmer (*23*) offer detailed descriptions of the copula-based approaches to statistical model estimation and the types of copulas available to generate multivariate distribution functions with given marginals; see also Genest and MacKay (*24*). A copula is a multivariate distribution function defined over the unit cube that links uniformly distributed marginals. Let C be an I-dimensional copula of uniformly distributed random variables $U_1, U_2, U_3, \ldots, U_I$ with support contained in $[0, 1]^I$. Then,

$$C_\theta\left(u_1, u_2, \ldots, u_I\right) = \Pr\left(U_1 < u_1, U_2 < u_2, \ldots, U_I < u_I\right) \quad (1)$$

where θ is a parameter vector of the copula commonly referred to as the dependence parameter vector. Consider I random variables $\epsilon_1, \epsilon_2, \epsilon_3, \ldots, \epsilon_I$, each with a univariate continuous marginal distribution function $F(z_i) = \Pr(\epsilon_i < z_i)$. (The univariate marginal distribution functions of the random variables do not have to be identical. Such a specification often is used, however, to develop econometric models where the random terms represent individual-level idiosyncratic effects.) A joint I-dimensional distribution function of the random variables with the continuous marginal distribution functions $F(z_i)$ can be generated as follows (*25*):

$$\begin{aligned} F\left(z_1, z_2, \ldots, z_I\right) &= \Pr\left(\epsilon_1 < z_1, \epsilon_2 < z_2, \ldots, \epsilon_I < z_I\right) \\ &= \Pr\left[U_1 < F\left(z_1\right), U_2 < F\left(z_2\right), \ldots, U_I < F\left(z_I\right)\right] \\ &= C_\theta\left[u_1 = F\left(z_1\right), u_2 = F\left(z_2\right), \ldots, u_I = F\left(z_I\right)\right] \end{aligned} \quad (2)$$

The above equation offers an approach to develop different dependency patterns for the random variables $\epsilon_1, \epsilon_2, \epsilon_3, \ldots, \epsilon_I$, based on the copula that is used as the underlying basis of construction. For purposes of this paper, a class of copulas referred to as the Archimedean copulas is used to generate the dependency between the random variables. The Archimedean class is popular in empirical applications, and includes a whole suite of closed-form copulas that cover a wide range of dependency structures, including comprehensive and noncomprehensive copulas, radial symmetry and asymmetry, and asymptotic tail independence and dependence, as discussed in detail by Nelsen (*26*) and Bhat and Eluru (*22*). This class of copulas is flexible and easy to construct.

Archimedean copulas are constructed on the basis of an underlying, continuous convex-decreasing generator function as discussed by Bhat and Eluru (*22*). A variety of Archimedean copulas have been identified on the basis of different forms of this generator function. In this paper, four of the most popular Archimedean copulas are considered that span the spectrum of dependency structures. These are the Clayton, Gumbel, Frank, and Joe copulas. [See Bhat and Eluru (*22*) for graphical descriptions of the implied dependency structures.] All of these copulas allow only positive associations and equal dependencies among pairs of random variables in their multivariate forms, which is well suited to cluster analysis where positive and equal dependencies are to be expected among the elements within a cluster. The Clayton copula (*27*) is best suited for strong left-tail dependence and weak right-tail dependence; that is, it is suitable when, after controlling for observed covariates, vehicle occupants tend to have a simultaneously high propensity for low—but not for high—injury severity levels. The Gumbel (*28*) copula (also referred to as the Gumbel-Hougaard copula) is well suited for strong right-tail dependence (strong correlation at high values) but weak left-tail dependence (weak correlation at low values); that is, it is suitable when, after controlling for observed covariates, vehicle occupants tend to have a simultaneously high propensity for high—but not for low—injury severity levels. Like the Gaussian (normal) copula, the Frank (*29*) copula is radially symmetric in its dependence structure. This copula is suitable for equal levels of dependency in the left and right tails, with strong clustering in the middle (much stronger than the Gaussian copula); that is, it is suitable when vehicle occupants tend to have a simultaneously high propensity for high—or for low—injury severity levels. The Joe (*30, 31*) is similar to the Clayton copula, but the right-tail positive dependence is stronger.

Model Formulation and Estimation

Let q be an index for clusters (vehicle in the current empirical context) ($q = 1, 2, \ldots, Q$), and let i be the index for occupants ($i = 1, 2, \ldots, I_q$, where I_q denotes the total number of occupants in vehicle q; in the study reported here, I_q varied between 1 and 5). Let k be an index for the discrete outcomes that correspond to the injury severity level. The index k, for example, may take the values of no injury ($k = 1$), possible injury ($k = 2$), nonincapacitating injury ($k = 3$), incapacitating injury ($k = 4$), and fatal injury ($k = 5$). In the usual ordered-response framework notation, the latent propensity can be written as (y^*_{qi}) of occupant i in vehicle q to sustain an injury severity level as a function of relevant covariates. It can then be related to the severity outcome (y_{qi}) by representing the injury severity sustained by occupant i in vehicle q through threshold bounds (*32*):

$$y^*_{qi} = \beta' x_{qi} + \epsilon_{qi} \qquad y_{qi} = k \qquad \text{if } \psi_k < y^*_{qi} \le \psi_{k+1} \quad (3)$$

where

x_{qi} = ($L \times 1$) vector of exogenous variables for occupant i in vehicle q (not including a constant),

β = corresponding ($L \times 1$) vector of coefficients to be estimated, and

ψ_k = the lower bound threshold for injury severity level

$$k\left(\psi_1 < \psi_2 \cdots < \psi_K < \psi_{K+1}; \psi_1 = -\infty, \psi_{K+1} = +\infty\right)$$

The ϵ_{qi} terms capture the idiosyncratic effect of all omitted variables for occupant i in vehicle q, and are assumed to be independent of β and x_{qi}. The ϵ_{qi} terms are assumed identical across occupants, each with a univariate continuous marginal distribution function $F(z_{qi}) = \Pr(\epsilon_{qi} < z_{qi})$. The error terms can take any parametric marginal distribution, although only the normal and logistic distributions are considered here. Because of identification considerations in the ordered-response model, the univariate distribution functions are standardized, so that they are standard normal or standard logistic distributed.

Dependence in the ϵ_{qi} terms across occupants i in the same vehicle q is accommodated to allow unobserved cluster effects. This dependency is generated through the use of an Archimedean copula on the basis of Equation 2, where the only difference now is the introduction of the index q to reflect that the dependence is confined to occupants of the same vehicle:

$$\begin{aligned} &\Pr\left(\epsilon_{q1} < z_{q1}, \epsilon_2 < z_{q2}, \ldots, \epsilon_{qI_q} < z_{qI_q}\right) \\ &\quad = \Pr\left[U_{q1} < F\left(z_{q1}\right), U_{q2} < F\left(z_{q2}\right), \ldots, U_{qI_q} < F\left(z_{qI_q}\right)\right] \\ &\quad = C_{\theta_q}\left[u_{q1} = F\left(z_{q1}\right), u_{q2} = F\left(z_{q2}\right), \ldots, u_{qI_q} = F\left(z_{qI_q}\right)\right] \end{aligned} \quad (4)$$

The level of dependence among occupants of a vehicle can vary across vehicles, as reflected by the θ_q notation for the dependence parameter. This dependence parameter was parameterized in this study as a function of observed vehicle characteristics. [It is possible to use different copula forms (i.e., dependency surfaces) for different vehicles; however, in this study, the same copula form was maintained across all vehicles to keep the estimation tractable.]

Let m_{qi} be the actual, observed categorical response for y_{qi} in the sample. Then the probability of the observed vector of injury severity levels across occupants in vehicle q $(m_{q1}, m_{q2}, m_{q3}, \ldots, m_{qI_q})$ can be written as

$$P\left(y_{q1} = m_{q1}, y_{q2} = m_{q2}, \ldots, y_{qI_q} = m_{qI_q}\right) = \int_{M_q} c_{\theta_q}\left(F\left(y^*_{q1}\right), F\left(y^*_{q2}\right), \ldots, F\left(y^*_{qI_q}\right)\right) dy^*_{q1}\, dy^*_{q2} \ldots dy^*_{qI_q} \quad (5)$$

where $M_q = \{y^*_{q1}, y^*_{q2}, \ldots, y^*_{qI_q} : \psi_{(m_{qi})} < y^*_{qi} < \psi_{(m_{qi}+1)}$ for all $i = 1, 2, \ldots, I_q\}$ and $c_{\theta q}$ = the copula density. The integration domain M_q is simply the multivariate region of the y^*_{qi} variables ($i = 1, 2, \ldots, I_q$) determined by the observed vector of injury outcomes $(m_{q1}, m_{q2}, \ldots, m_{qI_q})$. The dimensionality of the integration, in general, is equal to the number of occupants I_q in the vehicle. Thus, if a Gaussian copula is used, integrals are of the order of the number of occupants in the vehicle for the joint probability of the observed combination of the injury severity levels across occupants in the vehicle. This will necessitate the use of simulation techniques when I_q is greater than 3. In the case of a vehicle-level cluster with identical dependencies between pairs of occupants in the vehicle, however, the Archimedean copulas can be gainfully employed, since they provide closed-form, multivariate, cumulative distribution functions. In particular, the probability in Equation 5 can be written in terms of 2^{I_q} closed-form, multivariate, cumulative distribution functions as follows:

$$\begin{aligned}
&P\left(y_{q1} = m_{q1}, y_{q2} = m_{q2}, \ldots, y_{qI_q} = m_{qI_q}\right) \\
&= P\left(\psi_{m_{q1}} < y^*_{q1} < \psi_{m_{q1+1}}, \psi_{m2} < y^*_{q2} < \psi_{m_{q2+1}}, \ldots, \psi_{m_{qI_q}} < y^*_{qI_q} < \psi_{m_{qI_q}+1}\right) \\
&= \sum_{a_1=1}^{2}\sum_{a_2=1}^{2} \cdots \sum_{a_{I_q}=1}^{2} (-1)^{a_1+a_2+\cdots+a_{I_q}} \left[P\left(y^*_{q1} < \psi_{m_{q1}+a_1-1}, y^*_{q2} < \psi_{m_{q2}+a_2-1}, \ldots, y^*_{qI_q} < \psi_{m_{qI_q}+a_{I_q}-1}\right)\right] \\
&= \sum_{a_1=1}^{2}\sum_{a_2=1}^{2} \cdots \sum_{a_{I_q}=1}^{2} (-1)^{a_1+a_2+\cdots+a_{I_q}} \left[C_{\theta_q}\left(u_{m_{q1}+a_1-1}, u_{m_{q2}+a_2-1}, \ldots, u_{m_{qI_q}+a_{I_q}-1}\right)\right]
\end{aligned} \quad (6)$$

where $C_{\theta q}$ is one of the four Archimedean copulas discussed previously with an association parameter θ_q, and $u_{m_{qi}+a_i-1} = F(\psi_{m_{qi}+a_i-1} - \beta' x_{qi})$ The number of cumulative distribution function computations increases rapidly with the number of individuals I_q in vehicle q, but this is not much of a problem when the cluster sizes are 6 or less because of the closed-form structures of the cumulative distribution functions. In the current empirical context, $I_q \leq 5$, thus lending itself to the use of the copula-based approach for model estimation.

The association parameter θ_q is allowed to vary across vehicles. It is not possible, however, to estimate a separate dependence term for each vehicle. Therefore, θ_q is parameterized as a function of a vector s_q of observed vehicle variables, while a functional form is also chosen that ensures that θ_q for any vehicle q is within the allowable range for each copula: thus, $\theta_q = \exp(\delta' s_q)$ for the Frank and Clayton copulas; and $\theta_q = 1 + \exp(\delta' s_q)$ for the Gumbel and Joe copulas.

The parameters to be estimated in the model may be gathered in a vector $\Omega = (\beta', \delta', \psi')'$, where the vector ψ is the vector of threshold bounds: $\psi = (\psi_1, \psi_2, \ldots, \psi_K)$. The likelihood function for vehicle q may be constructed on the basis of the probability expression in Equation 6 as

$$L_q(\Omega) = P\left(y_{q1} = m_{q1}, y_{q2} = m_{q2}, \ldots, y_{qI_q} = m_{qI_q}\right) \quad (7)$$

The likelihood function to be maximized is then given by

$$L(\Omega) = \prod_q L_q(\Omega)$$

DATA

The study's crash data were derived from the 2007 GES as obtained from NHTSA (*2*). The GES data were compiled from a sample of police-reported accidents that involved at least one motor vehicle traveling on a roadway and that resulted in property damage, injury, or death. They were drawn from crashes in about 60 areas across the United States that reflected the geography, population, and traffic patterns of the country. A detailed discussion of the sampling and compilation of crash data for the GES is provided in the GES documentation available at the NHTSA website (http://www.nhtsa.gov). The 2007 GES includes information on 60,000 crashes that involved about 150,000 individuals and 100,000 vehicles. A number of crash-related attributes were collected for each record in the GES including, for example, driver and vehicle characteristics, roadway design attributes, environmental conditions, and crash characteristics. The injury severity of each individual involved in a crash was coded on a 5-point ordinal scale: (1) No injury, (2) possible injury, (3) nonincapacitating injury, (4) incapacitating injury, and (5) fatal injury.

Study analysis was confined to an examination of the severity of injuries sustained by occupants in noncommercial (private) passenger vehicles involved in collisions, (i.e., where a vehicle collided with a stationary object or another vehicle). The vast majority of crashes in the database involved one or two vehicles, and therefore, records in which three or more vehicles were involved in a crash were not included in the analysis. Through an extensive data checking and cleaning effort, the cases selected for analysis were limited to those for which complete information was available on all occupants involved in a given crash. The cleaned data set used in this study involved 35,978 vehicles and 48,004 occupants.

Because the data set was large, a random sample of records was drawn for the model estimation process. The random sample used included 5,297 occupants (4,000 drivers and 1,297 passengers) in 4,000 vehicles; and 77.3% single-occupant, 15.9% two-occupant, 4.3% three-occupant, 2.0% four-occupant, and 0.5% five-occupant crashes. Within each of the multiple occupant vehicles, 16 seat position configurations were possible for up to five occupants. The distribution of the occupants based on the seat position in this estimation sample was as follows:

- Driver: 75.5%,
- Front-seat passenger: 15.0%,
- Rear-left passenger: 3.5%,
- Rear-center passenger: 1.3%, and
- Rear-right passenger: 4.7%.

Table 1 presents a summary of the sample characteristics of the occupants of the vehicles involved in the crashes. More than three-quarters of the crashes involved two vehicles. The sample included

TABLE 1 Sample Characteristics

Characteristic	%
Occupants: male	52.1
0–15 years	8.6
16–20 years	17.1
21–45 years	46.3
46–65 years	20.2
65+ years	7.8
Wearing seat belt	92.0
Vehicles	
Sedan	59.2
SUV	17.2
Pickup truck	16.5
Van	7.1
Environment: time of crash	
12 a.m.–6 a.m.	6.9
6 a.m.–9 a.m.	13.3
9 a.m.–3 p.m.	32.3
3 p.m.–7 p.m.	32.2
7 p.m.–12 a.m.	15.3
Roadway: speed limit	
≤35 mph	41.2
35–55 mph	48.1
55+ mph	10.7
Crash	
Number of vehicles involved	
One vehicle	22.2
Two vehicles	77.8
Type	
Head-on	5.2
Rear-end	30.5
Sideswipe	5.9
Angle	36.2
Other (single-vehicle/ fixed-object crashes)	22.2

TABLE 2 Injury Severity Levels

Injury Outcome	Driver (%)	Passenger (%)	Overall (%)
No injury	66.0	65.8	65.9
Possible injury	13.0	15.0	13.5
Nonincapacitating injury	12.2	11.6	12.1
Incapacitating and fatal injury	8.8	7.6	8.5

a slightly higher fraction of males. Nearly one-half of the occupants were aged 21 to 45 years; children aged 15 years or less made up nearly 9% of the sample. Seat belt use was quite high; 92% of the occupants reported that they had buckled up. About 60% of the vehicles were sedans. Most of the crashes occurred at midday and in the evening, presumably because travel levels were higher during those periods. Each of these periods accounted for more than 30% of the crashes in the sample. About 90% of the crashes took place on roadways with speed limits of 55 mph or less. Head-on collisions accounted for only 5% of the crashes, whereas rear-end and angle collisions each accounted for more than 30% of the crashes.

The distributions of injury severity levels for the vehicle occupants are shown in Table 2. Nearly two-thirds of occupants (whether drivers or passengers) reported no injury. A little more than 10% of the occupants reported a possible injury or nonincapacitating injury in both the driver and passenger samples. The percent of individuals that sustained fatal injuries was extremely small in this random estimation sample (about 0.6%). To ensure a reasonable share for each alternative outcome, the incapacitating and fatal injury categories were merged to generate a single "serious injury" category. This category accounted for about 8.5% of the outcomes reported in the sample.

MODEL ESTIMATION RESULTS

This section presents model estimation results. Overall model specification considerations are presented, and model performance is described in terms of goodness-of-fit. Discussed in detail are the actual factors that affected the injury severity of multiple occupants in vehicle crashes.

Model Specification and Overall Performance

The model specification included a range of variables, which covered five broad categories of factors:

- Occupant characteristics including age, sex, alcohol state, and seat belt use;
- Vehicle characteristics including vehicle type;
- Environmental characteristics including day of week, time of day, lighting conditions, and weather conditions;
- Roadway design attributes including speed limit, type of roadway, roadway alignment, and number of lanes; and
- Crash characteristics including whether the occupant was ejected from the vehicle, whether the vehicle rolled over, whether it was a single-vehicle or two-vehicle crash, the collision type, and the role of the driver's vehicle in a two-vehicle crash.

The final model specification was derived from a systematic process to select variables for inclusion on the basis of statistical significance, intuitive interpretation, parsimony in specification, and consistency with results reported in previous studies of injury severity. Several combinations of variables, functional forms, and interaction terms were considered.

Four copula structures (Clayton, Gumbel, Frank, and Joe) were examined to specify the dependency between the ϵ_{qi} terms across vehicle occupants to represent the vehicle cluster effect, and two univariate distribution assumptions (normal and logistic) for the random error term ϵ_{qi}. For the sake of brevity, the results are presented only for the best copula model and the best independent model (from the logistic and the normal distributions for the ϵ_{qi} terms). To determine the best model among the copula models, the Bayesian Information Criterion (BIC) was employed; see Quinn (*33*), and Trivedi and Zimmer (*23*) for details. For a given copula model,

$$\text{BIC} = -2\ln(L) + M\ln(Q)$$

where

$\ln(L)$ = log likelihood value at convergence,
M = number of parameters, and
Q = number of observations.

The copula that results in the lowest BIC value is the preferred copula. The BIC-based selection procedure in the research effort was equivalent to a selection on the basis of the largest value of the log-likelihood function at convergence, because all of the competing models had the same exogenous variables and the same number of thresholds.

Among the copula models, the results indicated that the Probit-Frank (PF) model provided the best data fit with a likelihood value of −4677.9. In all of the copula models, however, the dependency parameters were highly statistically significant, with the vehicle-level dependency in unobserved factors varying on the basis of vehicle type. Specifically, the vehicle-level dependency was different across four vehicle types—sedan, SUV, pickup truck, and van. Between the two independent models, the normal error term distribution for the marginals [i.e., the ordered-response probit (ORP)] provided a slightly better fit than the logistic error term distribution for the marginal (i.e., the ordered-response logit). The likelihood ratio test, which compared the PF model in this study with the independent ORP model, yielded a test statistic value of 373.0. That value was substantially larger than the critical χ^2 value with 4 degrees of freedom (which corresponded to the four dependency parameters) at any reasonable level of significance. It confirmed the importance of accommodating dependence in injury severity propensity among vehicle occupants.

Key Findings

Model estimation was undertaken for all occupants together, while unobserved dependencies were accommodated in the latent injury propensities of occupants within a vehicle. Separate coefficients were estimated for the driver, front-seat passenger, and rear-seat passengers. Coefficients for all rear-seat passengers were restricted to be equal, given the small sample of rear-seat passengers. Indicator variables were included in the model specification, however, to allow for potential differences across rear-seat passengers. Model estimation results are presented in Table 3.

The coefficients presented in the table indicate the effects of variables on the latent injury severity propensity of an occupant. A positive coefficient associated with a variable indicates that the variable contributed positively to a higher injury severity propensity. The first set of values in the table present the thresholds of the ordered-response model, which simply serve to translate the latent propensity into the observed-ordered categories of injury severity. For the dummy variables (including variables with multiple levels), there is a reference category, which may vary by seat position category. As shown in Table 3, when all levels of a dummy variable were present, the coefficients with "—" represented the reference category. For other dummy variables, the reference category is identified explicitly in the table.

Among occupant characteristics, males had a lower propensity to sustain severe injuries when compared with females seated in the front row (either as drivers or passengers). When the driver was male, the front-seat passenger (who was more likely to be female) had a higher propensity to experience a severe injury. This finding confirms previous research [see Ulfarsson and Mannering (*5*)] and indicates significant gender differences (e.g., related to weight, body structure, or other factors) in injury severity outcomes after controlling for the factors usually available in injury severity analyses. Children aged 0 to 5 years were less likely to be severely injured when seated in the rear. Compared with older drivers (65+ years of age), younger drivers were less likely to sustain a severe injury. This was particularly so for the youngest group of drivers, who were 16 to 20 years of age. Older passengers (65+ years) seated in the front had a higher propensity to be severely injured compared with front-row passengers in other age groups. With an increasing number of elderly people in virtually every country of the world, many of whom are going to depend on others for transportation, this finding merits serious consideration for the implementation of countermeasures. The installation might be called for of special safety devices and equipment in vehicles that would protect the elderly, whose physical condition may be more fragile compared with that of other age groups.

As expected, seat belt use consistently resulted in a lower injury severity propensity. When the driver was under the influence of alcohol and behaved "recklessly," the propensity of severe injuries rose. A driver of a fully occupied vehicle appeared less likely to be severely injured, presumably because he or she was careful in light of the responsibility to transport a full vehicle of passengers, and perhaps because the passengers in turn ensured that the driver was careful in operating the vehicle. [As has been pointed out, careful driving would be more reasonably discovered in a crash rate analysis. It is,

TABLE 3 Vehicle Occupant Injury Severity Estimation Results

	Driver		Front Passenger		Rear Passenger	
Variable	Parameter	*t*-Stat.	Parameter	*t*-Stat.	Parameter	*t*-Stat.
Threshold Parameters						
Threshold 1	0.0195	0.154	0.4646	1.466	0.8537	5.086
Threshold 2	0.4660	3.669	1.0116	3.199	1.3423	7.414
Threshold 3	1.1114	8.617	1.6895	5.247	1.9510	10.245
Occupant Characteristics						
Male	–0.1644	–4.078	–0.1923	–2.483	—	—
Driver is male	—	—	0.1499	1.905	—	—
Occupant age (years)						
0–5	—	—	—	—	–0.6065	–4.453
16–20	–0.2710	–3.222	—	—	—	—
21–44	–0.1364	–1.955	—	—	—	—
45–64	–0.1364	–1.955	—	—	—	—
≥65			0.2649	1.944		
Driver age (base: <45 years): ≥45 years	—	—	0.2873	3.222	—	—
Seat belt used (base: seat belt not used)	–0.8629	–10.235	–0.5189	–3.016	–0.3072	–2.673
Driver under the influence of alcohol (base: no alcohol influence)	0.4067	4.797	—	—	—	—
Driver behavior characterized as “reckless” (base: not reckless)	0.5432	1.939	—	—	—	—
Number of occupants = 5	–0.7578	–3.010	—	—	—	—
Vehicle Characteristics						
Vehicle type (base: all other vehicle types): sedan	0.2051	4.853	0.1885	2.407	0.4104	3.409
Colliding vehicle type (base: all other vehicle types): sedan	–0.1266	–2.761	—	—	—	—
Rear-center indicator (base: other rear seat configuration)	—	—	—	—	–0.4146	–2.431
Environment Factors						
Time of crash (base: 7:00 p.m. to 12:00 midnight)						
12:00 midnight–6:00 a.m.	0.2405	3.373	—	—	—	—
6:00 a.m.–9:00 a.m.	0.1320	2.260	–0.3378	–2.228	—	—
9:00 a.m.–3:00 p.m.	—	—	–0.2734	–2.321	—	—
3:00 p.m.–7:00 p.m.	—	—	–0.2929	–2.530	—	—
Lighting condition (base: normal lighting)						
Dark with lighting	—	—	–0.3535	–2.883	—	—
Dark	—	—	—	—	—	—
Adverse weather and road condition (base: no adverse weather condition)						
Wet	–0.0992	–2.003	—	—	—	—
Snow	–0.0992	–2.003	–0.3154	–2.867	—	—
Ice	–0.0992	–2.003	—	—	—	—
Rain	—	—	–0.3154	–2.867	–0.2497	–1.621
Roadway Attributes						
Speed limit (base: ≤35 mph)						
35–55 mph	0.1779	4.097	0.2254	2.681	0.2136	1.669
>55 mph	0.3120	4.298	0.2254	2.681	0.6242	3.201
Traffic way without median	0.0920	1.975	0.1893	2.261		
Roadway alignment: curved road	0.1814	2.878	0.3905	3.062	—	—

(continued on next page)

TABLE 3 *(continued)* **Vehicle Occupant Injury Severity Estimation Results**

	Driver		Front Passenger		Rear Passenger	
Variable	Parameter	*t*-Stat.	Parameter	*t*-Stat.	Parameter	*t*-Stat.
Crash Characteristics						
Vehicle rolled over (base: no rollover)	0.8271	7.612	0.8150	4.150	0.9008	3.387
Occupant ejected from vehicle	1.4659	2.772	0.6602	0.998	—	—
Crash with stationary object (base: crash with another vehicle)	0.3919	5.572	0.5840	2.233	—	—
Role of vehicle in two-vehicle crashes (base: vehicle strikes the other vehicle)						
Contacted vehicle	0.1452	2.943	0.2782	3.022	—	—
Both striking and contacted vehicle	0.6340	4.447	0.5867	2.663	—	—
Type of collision (base: other type of crashes)						
Head-on	1.1335	12.029	1.3135	4.501	1.1508	4.169
Rear-end	—	—	0.3072	1.194	—	—
Sideswipe	−0.2848	−2.546	—	—	—	—
Angle	0.4230	8.014	0.7260	2.921	0.4169	3.315

NOTE: — = reference category when all levels of a dummy variable were present.

however, reasonable to assume that a person that drives defensively will incur less severe injuries in a crash. A recent study by Paleti et al. has found this to be the case (*34*).] It is also plausible that a careful driver might anticipate a crash and take evasive actions to reduce its severity, although other explanations for this result are possible. Travel in sedans is associated with a higher injury severity level than is travel in large SUVs, pickups, and vans. This finding is intuitive, as better protection from severe injury is to be expected in a large, heavy vehicle. Rear passengers seated in the middle section of a sedan had a propensity to experience a lower level of injury level than passengers seated elsewhere, suggesting that the middle rear is the safest position in the event of a crash. This finding is consistent with the literature (*13*).

Among environmental factors, time of day significantly affected injury severity levels. Occupants seated in the front row (whether drivers or passengers) were likely to sustain more severe injuries in crashes between midnight and 6:00 a.m. than at other times, a finding consistent with assumptions that driving in the dark presents more challenges and is more likely to be associated with alcohol consumption than at other times of days. Lighting installed along the roadway lowered the propensity for severe injury. In wet and snowy conditions, both drivers and front-row passengers had a lower injury propensity, presumably because vehicles proceeded at slower speeds, and drivers were more cautious under these conditions.

As expected, the injury severity for occupants in all positions was higher in crashes on roadways where the speed limit was higher than elsewhere. The absence of a median to divide the roadway and the presence of curves in the roadway contributed positively to the injury severity propensity for the driver and the front-seat passenger.

These findings have important implications for roadway design and alignment. Crashes in which the vehicle rolls over, the occupant is ejected from the vehicle, or the vehicle collides with a stationary object are associated with higher levels of injury severity, particularly for front-row occupants. When occupants are in a vehicle that strikes another vehicle and is struck itself, the likelihood of a severe injury rises substantially. This is signified by a higher positive coefficient than for a vehicle that strikes nothing but is hit by another vehicle. Consistent with expectations, head-on collisions and angle crashes showed high injury severity propensities for all vehicle occupants. Rear-end collisions were associated with a higher injury propensity for a front-seat passenger, whereas sideswipe collisions were associated with lower injury severity levels. Countermeasures to prevent head-on and angle crashes are likely to be the most effective means to reduce the injury severity levels associated with crashes.

Overall, the findings are consistent with expectations and speak to the important impact that observed factors have on injury severity levels. The findings confirm results reported previously in the literature and offer some insights into the types of safety countermeasures that can reduce injury severity levels of drivers and passengers seated in different positions. The study reported here, however, goes beyond what has been done previously to examine for possible unobserved dependence effects that can have a substantial impact on the values of model coefficients, if indeed such effects are present. The estimated copula-based, clustered ordered-response model incorporated the jointness in injury severity across vehicle occupants that may be caused by the presence of common unobserved factors. To ignore such dependencies completely or to pre-impose specific functional forms of the dependency can, and in general will, lead to inappropriate covariate influence estimates on injury severity levels.

Model Assessment and Validation

As indicated earlier, the Frank copula model form provided the best fit. The association parameter was parameterized in the Frank copula as $\theta_q = \exp(\delta' s_q)$ to accommodate potential heterogeneity in the dependence effects across clusters. Explicit recognition was given to the possibility that dependence effects in injury severity across vehicle occupants varied by vehicle type. Therefore, the s_q vector included four dummy vehicle type variables (i.e., sedan, SUV, pickup truck, and van). The implied Frank association parameter θ_q for these four vehicle types and their corresponding standard errors were computed by using the delta method; see Greene (*35*). The results were as follows: sedan, 5.2651 (2.023); SUV, 7.3068 (2.985); pickup truck, 7.6156 (3.244); and van, 4.3462 (1.152). All of these parameters were highly statistically significant (relative to the value of zero, which corresponds to independence) and indicated the strong dependence among the unobserved injury severity determinants of vehicle occupants.

Another common way to quantify the dependence in the copula literature is to compute the Kendall's measure of dependence, as Bhat and Eluru (*22*) describe in detail. The Kendall's measure of dependence takes the place of a traditional correlation coefficient when dealing with asymmetric distributions. For the estimated association parameters, θ_q, the values of the Kendall's measures were as follows: sedan, 0.473; SUV, 0.575; pickup truck, 0.588; and van, 0.413. These measures of concordance, coupled with the dependence form of the Frank copula, implied that the dependency was strong in unobserved components across occupants in the propensity to sustain an injury severity level. In particular, the highest level of dependence in injury severity from unobserved factors was for occupants of SUVs and pickup trucks. (Scatter plots were generated to illustrate the relationship between the unobserved components ϵ_{qi} of injury severity propensity for any two occupants in the same vehicle *q,* on the basis of vehicle type. Because of space constraints, these plots are not presented but are available from the authors.)

In an effort to further assess the PF model, a model validation effort was undertaken. The performance of the PF model was compared against that of the ORP model of independence for a validation sample that was not part of the estimation data set. The validation sample consisted of 1,000 vehicles and 1,365 occupants. To perform the validation, the predictive log likelihood measure was computed for both models for various subsamples. The results of the validation effort are presented in Table 4.

An examination of the results of the validation exercise confirmed that the PF model clearly offered a superior statistical fit and predictive power than the ORP model of independence. The likelihood ratio test presented in the last column offers a statistical basis on which to compare the performance of the PF model with that of the ORP model. For the full sample, and most subsamples considered in the table, the PF model was statistically significantly better than the ORP model. The PF model performed substantially better than the ORP model when the vehicle had multiple occupants (particularly when there were three or four). This finding is consistent with expectations that the correlation across dimensions would be substantive only for vehicles that had multiple occupants. The PF model showed a statistically significant superior data fit for one-vehicle and two-vehicle crashes, sedan and SUV crashes, crashes on roadways with a speed limit between 35 and 55 mph, and for rear-end collisions. The PF and the ORP models did not provide significantly different fit measures for other subsamples (e.g., head-on collisions and crashes on roadways with a speed limit of 35 mph or less, or where the speed limit was greater than 55 mph).

CONCLUSIONS

There is substantial interest in the profession to understand and identify factors that contribute to the severity of the injuries sustained by vehicle occupants in crashes. Past research has focused on the injury severity of the occupant most severely injured in a crash and not on the injury severity levels of all of the occupants of a crashed-involved vehicle. While studies have examined the injury severity level of vehicle occupants by seat position, virtually no study has simultaneously analyzed the injury severity levels of all vehicle occupants in a crash. Initial attempts to do so have been limited to examinations of the injury severity of two vehicle occupants by using bivariate probit models, as reported by Yamamoto and Shankar (*8*). The ability to examine additional vehicle occupants simultaneously has been seriously hampered by methodological challenges associated with jointly modeling multidimensional phenomena with complex error correlation structures.

TABLE 4 Disaggregate Measures of Fit in Validation Sample

Sample Detail	Number of Observations	ORP Predictive Likelihood	PF Predictive Likelihood	Predictive Likelihood Ratio Test ($\chi^2_{4,0.05} = 9.49$)
Full validation sample	1,000	−1,213.02	−1,191.53	42.98
Number of occupants				
One	759	−643.70	−645.29	−3.17
Two	154	−301.70	−298.54	6.31
Three	54	−133.63	−126.10	15.06
Four	27	−101.17	−85.99	30.36
Five	6	−32.83	−35.61	−5.57
Number of vehicles				
One	198	−266.81	−256.87	19.86
Two	902	−946.21	−934.66	23.12
Vehicle type				
Sedan	574	−725.14	−717.17	15.94
SUV	176	−238.77	−227.46	22.61
Speed limit				
≤35 mph	394	−424.35	−420.40	7.90
35–55 mph	474	−593.95	−572.69	42.52
>55 mph	132	−194.72	−198.44	−7.42
Collision type				
Head-on	49	−85.89	−84.77	2.24
Rear-end	319	−323.03	−308.34	29.37

In this study, an ordered PF copula model was specified and estimated to allow for the joint modeling of injury severity outcomes for all occupants in a vehicle. The three major objectives were to account for the following:

1. The presence of common unobserved factors (error correlations) that simultaneously affected the injury severity outcomes of multiple occupants in a crash-involved vehicle;
2. The differential effects of various exogenous factors on injury severity according to the seat position of the vehicle occupant; and
3. The heterogeneity in injury severity dependency effects among vehicle occupants across vehicle types, which was done by parameterizing the copula association parameter as a function of vehicle body type.

The specification and estimation of such a model system is this study's contribution to the earlier research done in this area. A random sample of the 2007 GES data set was used to estimate the ordered-probit Frank copula model. The performance of the Frank copula-based model was compared against that of the ordered-probit–logit model of independence. It was found that the copula-based model that accommodated unobserved common determinants consistently outperformed the model of independence for virtually every subsample of crashes considered in the study reported here. The findings clearly point to the presence of correlated unobserved factors that determined the crash injury severity outcomes of multiple occupants in a vehicle and that the degree of correlation varied by vehicle body type. Models that ignored or neglected the presence of such common unobserved factors provided a poorer fit, and therefore were inferior in their predictive power.

From a safety perspective, the findings of this paper have important implications. First and foremost, the findings suggest that crash studies that model or predict injury severity levels associated with a transportation facility should consider the adoption of approaches wherein the injury severity levels of all vehicle occupants are modeled simultaneously or jointly. In this way, a more complete picture would be obtained of the injury severity profile associated with a facility, and countermeasures could be devised to address the entire profile of crash-related injuries. The use of a joint equations model, such as the one presented here, would allow this to be done while accounting for correlated unobserved factors often not present in safety data sets (e.g., speed of travel at the time of the crash, vehicle condition).

Model estimation results presented in the paper offer key insights into factors that affect crash severity levels for multiple occupants by seat position. The results have important implications for passenger safety and vehicle design. Consider, for example, that females in the front row are more likely to be severely injured than males. Females and older individuals in the front passenger seat are more likely to suffer severe injuries compared with other demographic groups. It would behoove the profession and vehicle manufacturers to consider the enhancement of safety devices and vehicular designs and ergonomics to better accommodate the physical characteristics of females and older individuals. The finding that higher injury severity levels are associated with riding in a sedan implies that vehicle manufacturers need to enhance safety features in smaller cars. Vehicle designs need to be enhanced to extend the safety of the rear-center seat position to other seat positions as well. Designs that minimized vehicle rollover and occupant ejection would lower the propensity to experience severe injury levels. The benefits of seat belt use and the dangers associated with alcohol consumption confirmed many findings reported in the literature. Safety and education campaigns that raise awareness of these issues are likely to have a beneficial impact on the reduction of injury severity levels.

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