Exploring the Temporal Variability of the Factors Affecting Driver Injury Severity by Body Region Employing a Hybrid Econometric Approach

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ABSTRACT
The current study contributes to safety literature by incorporating the influence of temporal factors (observed and unobserved) within a multivariate model system for medical professional generated body region specific injury severity score. For this purpose, we adopt a hybrid econometric modeling approach that accommodates for the unobserved factors using two mechanisms. First, we parameterize unobserved temporal factor variation through the customization of the variance by time cohort (heteroscedasticity). Second, the common unobserved factors affecting severity across various body regions is accommodated through traditional random parameter consideration process. The proposed model system is estimated using data drawn from the National Automotive Sampling System-Crashworthiness Data System (NASS-CDS) database for the time cohorts 2003, 2006, 2009, 2012, and 2015. For the current analysis, we consider 6-point Abbreviated Injury Scale (AIS) for eight body regions (head, face, neck, abdomen, thorax, spine, lower extremity, and upper extremity). The proposed model system offers interesting insights on body region severity evolution over time. The model estimation is augmented with post-estimation exercises including hold-out sample validation analysis, illustrative policy analysis and extensive elasticity effect computation.

Keywords: Temporal Variability; Body regions; NASS-CDS; Driver injury severity; Hybrid econometric approach; Abbreviated Injury Scale

1 INTRODUCTION AND MOTIVATION

With growing urbanization and vehicle adoption in the world, it is not surprising that traffic crashes continue to increase. According to the World Health Organization (WHO), traffic crashes resulted in nearly 1.35 million fatalities and 50 million injuries in 2018 (WHO, 2018). A major analytical tool considered for understanding the various factors affecting crash occurrence and crash consequence include econometric models for crash frequency and crash severity. In the current study, we focus on crash severity models that examine the impact of various independent variables on the consequence of the crash (conditional on its occurrence). Researchers in the safety field have contributed substantially to development of advanced statistical models to identify the factors affecting crash severity and quantify their impact on severity. Specifically, these studies have contributed to evaluating the impact of roadway design, driver demographics and behavior, vehicle characteristics, roadway characteristics, crash characteristics and environmental factors (see Marcoux et al., 2018; Mannering, 2018 for more details) on crash severity. The current study contributes to safety literature by incorporating the influence of temporal factors (observed and unobserved) within a multivariate model system for medical professional generated body region specific injury severity score.

While significant strides have been made methodologically in understanding crash severity, many of these studies analyzed police reported crash databases that adopt the five-level severity scale: fatal (K), incapacitating (A), non-incapacitating (B), possible injury (C), and property damage only (O). The applicability of these model frameworks developed is affected by the challenges associated with police reported data including underreporting of minor crashes, and discrepancies associated with police injury assessment (see Kabli et al., 2020 for a detailed discussion). Recognizing these limitations of police reported data, several research efforts advocate for the adoption of severity data compiled by medical professionals. The commonly employed severity scale in the medical field is the body region specific Abbreviated Injury Scale (AIS) a 6 points ordinal scale defined as minor, moderate, serious, severe, critical, and maximal injury (Gennarelli and Wodzin, 2008). Kabli et al. 2020 presented a comprehensive review of AIS based severity studies. While multiple study efforts considered AIS in modeling severity, the dependent variable characterization in these studies was either a single body region or an aggregated measure of AIS (such as AIS $\geq$3). The modeling approaches employed for AIS analysis include descriptive analysis, linear regression, logistic regression and ordered logit regression (see Kabli et al., 2020 for a comprehensive review of AIS based severity studies). Kabli et al. 2020 developed the first multivariate model of body region specific injury severity recognizing the presence of common observed and unobserved factors affecting severity across different body regions for an individual.

In this study, we build on Kabli et al. 2020 to incorporate the influence of temporal factors on parameters influencing body region specific severity. To elaborate, we adapt the proposed multivariate body region specific model to accommodate for temporal factors – observed and unobserved on severity. To be sure, it is important to highlight that the importance of temporal factors has been well recognized in transportation safety literature in recent years (Mannering, 2018; Marcoux et al., 2018; Hu et al., 2013; Wang et al., 2019; Tirtha et al., 2020). In the area of severity analysis, temporal evolution approaches have been considered for modeling police-reported injury severity. In these studies, the injury severity variable is considered as either a binary variable or a polychotomous variables (more than two levels). Studies employing binary representation rely on binary logistic regression and its variants (see Sze and Wong, 2007; Dabbour, 2017; Dabbour et al., 2019). Studies relying on polychotomous severity representation have considered random parameters models and their variants (such as heterogeneity in means and variances) see (Behnood and Mannering, 2019; Islam and Mannering, 2020; Islam et al., 2020), scaled and mixed generalized ordered logit models

(Marcoux et al., 2018), mixed multinomial logit model (Behnood and Mannering, 2015; Yu et al., 2020a; Alnawmasi and Mannering, 2019; Islam and Mannering, 2021), and latent class models (Yu et al., 2019). These studies have considered crashes by various modes such as pedestrian crashes (Guerra et al., 2020; Sze and Wong, 2007; Liu et al., 2019), motorcycle crashes (Alnawmasi and Mannering, 2019), truck crashes (Behnood and Mannering, 2019) and passenger vehicles (Al-Bdairi et al., 2020; Yu et al., 2020b; Marcoux et al., 2018).

The current study contributes to literature by translating these temporal factor consideration-based methods to a body region specific context with multiple dependent variables. The reader would recognize that in all the police reported injury-based studies, the model system was based on a single injury severity variable. However, in the body region specific context, the presence of multiple body regions increases the complexity of the modeling process. Specifically, we need to accommodate for unobserved factor interaction across the individual (between various body regions) and temporal factors across cohorts. Specifically, the dimensionality of the unobserved factor interaction increases rapidly as a function of number of body regions and data time cohorts. In our study context, we have 8 body regions and five-time cohorts. It is possible to employ a random parameters-based approach to estimate the potential dependencies across these dimensions. However, the approach would result in a very high number of random parameters being estimated. To address the potential challenge of estimating unobserved interactions of about 40 dimensions, we adopt a mechanism that does not rely only on simulation in the model formulation. Specifically, we adopt a hybrid approach that parameterizes temporal factor variation through the customization of the variance by time cohort (heteroscedasticity) while the interactions across various body regions is accommodated through traditional random parameter process. The proposed approach would circumvent the need for resorting to exploding simulation-based error estimation for the influence of all unobserved factors. The proposed approach builds on earlier efforts for single dependent variable that have been adopted in transportation (Bhat, 1995; Anowar et al., 2016; Hahn et al., 2016) and safety literature (see Wang and Kockelman, 2005; Lemp et al., 2011; Marcoux et al., 2018; Tirtha et al., 2020 for examples of heteroscedastic models for single variable). The proposed model system is developed using a nationally representative crash sample provided in National Automotive Sampling System-Crashworthiness Data System (NASS-CDS) database for the time cohorts 2003, 2006, 2009, 2012, and 2015. NASS-CDS data includes police data along with the injury severity levels of patients, with detailed AIS scores by body region. In summary, the proposed research develops a hybrid multivariate model structure with eight body region specific injury variables across five time cohorts. The body regions considered include head, face, neck, abdomen, thorax, spine, lower extremity, and upper extremity. The proposed model system offers interesting insights on body region severity evolution over time. The proposed model system also provide support to the ordered model system application for injury severity analysis (see Eluru, 2013, Yasmin and Eluru, 2013 for a discussion on this comparison). An unordered model framework application using mixed multinomial logit model (or similar variants) for 8 body regions would be substantially more cumbersome resulting in an explosion of potential unobserved factors to be considered in model estimation with little to no gain in model explanation power. The simplicity of the ordered model system with a single propensity allows for a substantially parsimonious model system for observed and unobserved factors.

The rest of the paper is organized as follows: Section 2 provides details of the econometric model framework used in the analysis. In Section 3, the data source and data preparation procedures along with the variables considered are described. The model specification and the model estimation results are discussed in section 4. Section 5 provides a discussion of post-estimation exercises. Section 6 concludes the paper and highlights the research limitations.

2 ECONOMETRIC FRAMEWORK

In the current research effort, the modeling of injury severity levels for different body regions is undertaken using the Multivariate Scaled Random Parameters Generalized Ordered Probit model. In this section, we provide a description of our proposed model structure.

Let us assume i ($i = 1,2,3, \dots, N, N = 7{,}000$) be an index to represent the drivers (observation unit); $r(r = 1,2, \dots, R, R = 8)$ be an index for different body regions; $t(t = 1,2, \dots, T, T = 5)$ be an index of the year (1 = 2003, 2 = 2006,…. and 5 = 2015) and k ($k = 1,2,3, \dots, K$) be the index to represent injury categories at observation unit i for body regions r. In this empirical study, k take the values of 'no injury' ($k = 1$), 'minor injury' ($k = 2$), 'moderate injury' ($k = 3$), 'serious injury' ($k = 4$). The reader would note that based on sample size, we consider a different number of injury categories across different body regions (see Section 3 for exact details). In the ordered outcome framework, the actual injury severity (y_{irtk}) is assumed to be associated with an underlying continuous latent variable (y^*_{irt}). The latent propensity equation is typically specified using the following linear function:

$$y^*_{irt} = (\alpha_r + \gamma_{irt}) z_{irt} + \eta_{irt} + \xi_{irt} \quad (1)$$

This latent propensity y^*_{irt} is mapped to the actual injury categories y_{irtk} by the $\psi_{r,k}$ thresholds ($\psi_{r,0}$ =-∞ and $\psi_{r,K}$= ∞). z_{irt} is a vector of attributes that influences the propensity associated with injuries across different body regions. α_r is a corresponding vector of mean effects, and γ_{irt} is a vector of unobserved factors on injury propensity for driver i for body region r time cohort *t* assumed to be a realization from a normal distribution: $\gamma \sim N(0, \sigma^2)$. ξ_{irt} is an idiosyncratic random error term assumed to be identically and independently standard normal distributed across driver i. η_{irt} captures unobserved factors that impact injury severities across different body regions for driver i and time cohort *t*. Here, it is important to note that the unobserved heterogeneity between severities across different body regions and temporal points can vary across drivers. Therefore, in the current study, the correlation parameter η_{irt} is parameterized as a function of observed attributes as follows:

$$\eta_{irt} = \delta \; x_{irt} \quad (2)$$

where, x_{irt} is a vector of exogenous variables that identify potential correlation structures across all body regions (r), δ is a vector of unknown parameters to be estimated. The reader would note that there are no variables that vary by body region. However, unobserved factors can be introduced across different sets of body regions. For example, body region neck and abdomen can have one error correlation; body region lower extremity, and upper extremity can have a different correlation. These relationships can be introduced only when we allow for body region specific data columns (x_{irt}).

The generalized ordered probit model relaxes the constant threshold across observation to provide a flexible form of the ordered probit model. For this purpose, the thresholds are expressed as:

$$\psi_{r,k} = fn(s_{irtk}) \quad (3)$$

where, s_{irtk} is a set of exogenous variables (including a constant) associated with k th threshold. Further, to ensure the accepted ordering of observed injury severity $\left(-\infty < \psi_{r,1} < \psi_{r,2} < \dots\dots\dots < \psi_{r,K-1} < +\infty\right)$, we employ the following parametric form as employed by (Eluru et al., 2008):

$$\psi_{r,k} = \psi_{r,k-1} + exp((\beta_{r,k} + \theta_{irtk})s_{irtk}) \quad (4)$$

where, $\beta_{r,k}$ is a vector of parameters to be estimated. θ_{irtk} is another vector of unobserved factors moderating the influence of attributes in s_{irtk} on the injury severity k for analysis unit i body region r and time cohort *t*.

Given these relationships across different parameters, the resulting probability for the GOP model takes the following form:

$$P_{irtk} = G\left[\frac{(\psi_{r,k} - \{(\alpha_r' + \gamma_{irt'})z_{irt} + \eta_{irt}\}}{\lambda}\right] - G\left[\frac{(\psi_{r,k-1} - \{(\alpha_r + \gamma_{irt})z_{irt} + \eta_{irt}\}}{\lambda}\right] \quad (5)$$

where, $G(\cdot)$ is the standard normal cumulative distribution function (Eluru et al., 2013; Anowar et al., 2016), $\boldsymbol{\lambda}$ is the scale parameter of interest and is parameterized as exp(σ * l_{irt}) and l_{irt} is a vector of independent variables affecting the variance across the analysis year (2003, 2006, 2009, 2012, and 2015). For identification purposes, $\boldsymbol{\lambda}$ has to be set to 1 for at least one time period. If the parameters σ are insignificant the result would indicate that there is no variation in variance across the time cohorts.

In estimating the model, it is necessary to specify the structure for the unobserved vectors $\gamma, \delta,\ \theta\ and\ \eta$ represented by Ω. In this paper, it is assumed that these elements are drawn from independent normal distribution: $\Omega \sim N(0, (\sigma^2, \pi^2, \varrho^2,\ \rho^2))$. Thus, conditional on Ω, the likelihood function for the joint probability can be expressed as:

$$L_i = \int_{\Omega} \prod_{r=1}^{R} \prod_{t=1}^{T} \prod_{k=1}^{K} (P_{irtk})^{d_{irtk}} f(\Omega)\, d\Omega \quad (6)$$

where, d_{irtk} is a dummy variable taking the value 1 if the driver i sustain an injury level k for body region r in time cohort *t* and 0 otherwise. Finally, the log-likelihood function is:

$$LL = \sum_{i} Ln(L_i) \quad (7)$$

All the parameters in the model are estimated by maximizing the logarithmic function *LL* presented in equation 7. The parameters to be estimated in the model are: $\alpha, \beta, \psi, \sigma, \pi, \delta, \theta$ and ρ. To estimate the proposed model, we apply Quasi-Monte Carlo simulation techniques based on the scrambled Halton sequence to approximate this integral in the likelihood function and maximize the logarithm of the resulting simulated likelihood function across individuals. See (Bhat, 2001; Eluru et al., 2008) for examples of Quasi-Monte Carlo approaches in literature). The model estimation routine is coded in GAUSS Matrix Programming software.

3 DATA PREPARATION

The data for the current study is sourced from the National Automotive Sampling System-Crashworthiness Data System (NASS-CDS) database for the time cohorts 2003, 2006, 2009, 2012, and 2015. The NASS-CDS data is a nationally representative sample of road crashes provided by the National Highway Traffic Safety Administration (NHTSA) compiled from 24 geographic sites in the USA and draws from crashes resulting in the towing of at least one vehicle in the crash scene. For the five cohorts selected, the dataset includes information on 14,919 crashes involving 45,459 individuals and 29,776 vehicles. The selection of the different cohorts was based on two reasons. *First*, we wanted to consider a long-time horizon to

incorporate the influence of temporal factors on body region specific severity profile. Hence, we considered data from 2003. *Second*, we selected time periods at 3-year intervals to allow for reasonable sample size for the model estimation process. In our analysis, we only studied drivers and excluded all other passengers. As discussed in Kabli et al., 2020, consideration of all vehicle occupants would substantially increase the complexity of the model estimation process. The final sample prepared for modeling has 22,141 drivers. These drivers were split into two datasets: 1) model estimation sample with 7,000 drivers (1,400 from each time cohort uniformly as the previous research approach (see Marcoux et al, 2018)) and 2) holdout sample with 15,141 records ((2003: 5,149 observations, 2006: 5,326 observations, 2009: 3,155 observations, 2012: 1,174 observations, 2015: 377 observations) for validation analysis.

For the current analysis, we consider a total of eight body regions (head, face, neck, abdomen, thorax, spine, lower extremity, and upper extremity) while using the AIS scale for injury severity levels. The dataset provides information on six AIS scale ranging from 1 to 6 with 1 being no injury and 6 being the maximal injury. However, due to the limited sample size, some injury severity categories are grouped together for some body regions. The final data has four injury severity levels for the head (no injury, minor injury, moderate injury, and serious injury), two for neck (no injury and minor injury), and three for the other six body regions considered for the analysis (no injury, minor injury, and moderate injury). Further, there are some instances where drivers suffered more than one injury in the same body region. For example, a driver involved in the crash might suffer two different kinds of injuries in the right and left sides of the head. In such instances, we retained the maximum injury severity for that particular body region. Figure 1 presents the frequency distribution of injury severity for the five cohorts by each body region. Figure 1 highlights the improving safety of vehicle drivers (in the event of a crash) in recent years as indicated by the increasing share of the no-injury category across all the body regions from 2003-2015 (possibly because of the advancement and installation of safety tools in newer cars).

3.1 Variables Considered

The final dataset contains various independent variables that are categorized into five major groups: driver characteristics (including driver gender, driver age, seatbelt usage, alcohol consumption, and ejection status), vehicle characteristics (including vehicle type, vehicle age at time the crash happened, rollover, and steering airbag deployment), crash characteristics (including six crash types with two interactions), roadway characteristics (including traffic control type, speed limit, road alignment, traffic flow, and crash location), and environmental characteristics (including light condition and weather). In terms of temporal variables, we introduced a variable called "time elapsed from 2003" which is the time difference between the most recent years (2006, 2009, 2012, and 2015) from the base year (2003) considered in the current study context. Both linear and square effects of the time elapsed were tested. Moreover, the interaction of exogenous variables with the time elapsed variable (linear and square) were utilized to control for time varying variable effects. By employing this approach, we can accommodate for changes in temporal effects by year. Further, this will allow us to accommodate for capturing temporal impacts in the intermediate years not considered in our model. Finally, a summary of the sample characteristics of the explanatory variables is presented in Figure 2 and Figure 3. The datasets were prepared so that all years had the same set of independent variables and the same number of levels in each category for each body region. The reader would note that the crash type was classified employing the same method employed in (Kabli et al., 2020).

4 EMPIRICAL ANALYSIS

4.1 Model Specification and Overall Measure of Fit

The empirical analysis involves the estimation of three different model systems for driver severity for the eight body regions: 1) a set of Independent Scaled Ordered Probit models (ISOP), 2) a set of Independent Scaled Generalized Ordered Probit Models (ISGOP) and 3) Multivariate Scaled Random Parameters Generalized Ordered Probit model (MSRPGOP). The log-likelihood values (Bayesian Information Criterion) at convergence for the different models are as follows: 1) ISOP (152 parameters) is -29076.38 (59498.51), 2) ISGOP (160 parameters) is -29009.29 (59435.16) and 3) MSRPGOP (161 parameters) is -28513.87 (58453.18). The log-likelihood and BIC values clearly indicate that MSRPGOP model outperforms both ISOP and ISGOP.

4.2 Model Estimation Results

The estimation results of the proposed hybrid econometric model are presented in Table 1. For the ease of presentation, we provide a discussion of model results by variable groups.

4.2.1 Threshold Variables

The threshold parameters serve as delineators between alternatives in the ordered outcome model. The number of thresholds vary based on the number of severity levels modeled for each body region. These parameters do not have any substantive interpretation.

4.2.2 Temporal variables

Regarding temporal variables, we tested linear and square effects of the time elapsed variables for all body regions in our model. Only the linear time elapsed variable provides a significant effect on driver injury severity outcomes. Particularly, the linear specification of the time elapsed variable is found to be significant in the propensity for all body regions (with the exception of the neck region). The effect in the propensity for the linear time elapsed variable has a negative sign indicating a negative effect on driver injury severity in recent years for those body regions. The overall improvement in the severity profile over time (holding everything else same) is perhaps indicative of improvements in vehicle safety features, and roadway infrastructure improvements over time. In our analysis, only the abdomen region is found to have a positive temporal impact; potentially highlighting that driver injury severity propensity for the abdomen region is likely to have increased in recent years. The finding warrants consideration from vehicle manufacturers for potential changes in vehicle design over this time and future research studies examining driver body-region specific severity.

4.2.3 Driver Characteristics

It was found that younger drivers have a lower risk of abdomen and thorax regions injury risk compared to other drivers. However, senior drivers are likely to experience severe face, thorax, abdomen, spine, upper and lower extremities injury risk. These results are consistent with previous research that has identified age as a significant determinant of severity (Marcoux et al., 2018; Kabli et al., 2020). In the model specification, we also tested for the evolution of age-related impacts over time. However, we did not find any meaningful differences over time. Male drivers are found to be consistently associated with lower injury propensity across neck, abdomen, thorax, spine, upper and lower extremity regions. The result is similar to findings from several severity studies that indicate that male occupants injured in crashes are likely to sustain less severe injuries (see Yasmin and Eluru, 2013; Yan et al., 2021).

The variable representing alcohol consumption highlights additional injury risk for head and face regions. Further, the finding associated with using seat belts indicates that unrestrained drivers experience higher risk propensity across all body regions. Interestingly,

the model captured a negative sign for the threshold demarcating the minor and moderate injury for lower extremity region. The reader would note that the impact of the threshold parameter will need to be considered along with the propensity parameter to determine the overall impact. In a non-linear system, it is not easy to make the conclusion simply based on the coefficients without marginal/elasticity effects.

4.2.4 Vehicle Characteristics

With respect to vehicle characteristics, our results show that drivers in newer vehicles (less than three years old at the time the crash occurred) are likely to experience reduced injury risk, particularly for head, face, abdomen, thorax, and lower extremity regions. For the same variable, we also found a positive impact of the vehicle age variable on the threshold between minor and moderate injury for abdomen region reducing the probability of severe injury. It can be seen from Table 1 that drivers in utility vehicles have a lower injury risk propensity for head and thorax compared to other automobiles. Further, light trucks provide increased protection to drivers from severe injury in the head, face, abdomen, thorax, and lower and upper extremity regions. Consistent with previous findings (Howson et al., 2012; Khan and Vachal, 2020; Yu and Long 2021), our model found that drivers involved in a rollover crash have a higher risk propensity across all body regions. In our analysis, we also found a negative impact of rollover crash on the threshold value demarcating the minor and moderate injury for the spine indicating a higher risk of moderate injury and above in a rollover crash.

In the event a driver is ejected from a vehicle, the results indicate a higher injury risk propensity across all body regions. In our study, we found that a deployed steering airbag indicates an injury risk for all body regions. The finding needs to be cautiously considered. The result is possibly a reflection of endogeneity of steering airbag deployment with higher injury severity. Previous research has discussed the impact of airbag deployment for minor injury (see Wallis and Greaves, 2002; Gabauer and Gabler, 2010; Corazza et al., 2004; Shakouri and Mobini, 2019 for more details). The variable also has parameters affecting the threshold values for head and face regions. The reader would note that the parameters for face in the propensity and threshold parameters jointly influence the actual risk profile and it is not straight forward to isolate the exact impact on all severity levels. Finally, a positive sign for the steering air bag evolution over time in face and upper extremity indicates higher risk for these body regions over time.

4.2.5 Crash Characteristics

In earlier literature, the type of collision has always impacted the driver injury severity outcome. The current study finds that drivers involved in roadside departure collision type encounter a higher risk of serious injury for head and lower and upper extremity regions. Further, we found that the impact of this crash type (roadside departure) has significant variability on the injury propensity for upper extremity as indicated by the significant standard deviation. The result implies that the overall impact is likely to be positive (increased risk of injury) for about 68% of the drivers. The parameter for any forward impact (the driver involved in any type of crash involving a collision in the front part of the vehicle) shows that drivers involved have lower chance of being severely injured in the head, face, abdomen, thorax, spine, and lower extremity regions. However, the positive coefficient of any forward impact collision on the threshold value for thorax indicates increased propensity of minor injury in the thorax for a driver involved in a forward impact collision. To further examine the influence of forward impact, the impact of the interaction of the variable with head-on (both vehicle involved in head on crash) and rear-end crash types (the driver hit his/her frontal vehicle by the rear of the vehicle) is explored. The parameter estimates indicate that for rear-end collision all body regions (except spine) have lower propensity of injury. For backward impact collision (the

driver hit from behind), the estimated results highlight an increased propensity for injury for spine region and a lower injury risk for the face, abdomen, thorax, and lower extremity. Consistent with expectation, our results indicate that when struck by other vehicles on the driver side compared to the impact on the passenger side and other crash types, the likelihood of a severe injury substantially rises for head neck and upper extremity region (see Marcoux et al, 2018 for a similar finding). Further, the effect of driver side impact on the threshold value demarcating the minor and moderate injury indicates that driver involved in a driver side crash has higher injury risk in the upper extremity.

4.2.6 Roadway Characteristics

Posted speed limit serves as a surrogate measure of actual vehicle speed at the point of impact and the results show that the likelihood of being severely injured across the body regions (except face) are higher for drivers involved in a crash on high speed roads ($\geq$ 50mph). Further, a negative sign of threshold demarcating the moderate and serious injury indicates higher likelihood of moderate and severe injury for the head region. Driving on a road with a divided barrier increases the likelihood of being severely injured in the neck while reducing the risk propensity for thorax, spine and lower extremity. However, when the traffic flow is one way, the risk of injury for face, spine and upper extremity is found to be lower. This is intuitive as driving on a one-way road provides a more safer driving environment. Neck, abdomen, thorax and spine regions are much likely to have a serious injury when crash occurs on a curved road A crash at a stop sign increases the likelihood of abdomen and upper extremity injuries. Finally, crashes occurring at the intersection locations (compared to non-intersection locations) have a lower likelihood of being severely injured in face, abdomen, and thorax regions.

4.2.7 Environmental Characteristics

Many environment variables were examined in this study. However, only two variables provided significant parameters across different body regions. Crashes occurring in dark light condition (compared to crashes during daylight) increases the propensity of head, face, abdomen, and lower extremity injury. However, drivers involved in a crash during rainy weather are likely to have a reduced injury risk in the head, abdomen and thorax regions, perhaps a result of the cautious driving during rainy weather.

4.2.8 Scale Parameter

The variance of the unobserved segment for each year is represented by the scale parameter. As shown in Table 1, the linear time elapsed variable is found to be statistically significant for four body regions. When analyzing the unobserved factors across the years, the scale parameter indicates a significant variation. The variance of unobserved factors has reduced with time for abdomen, upper and lower extremity body regions, while the corresponding variance has increased over time for the spine region. The results support our hypothesis that significant variability exists in the variance of the unobserved component of body region injury severity propensity across cohorts.

4.2.9 Correlations

The final set of variables in Table 1 correspond to the correlation matrix (random parameters based unobserved heterogeneity) in the joint model. Three common unobserved factors were found to be significant. The first parameter represents the common unobserved factors affecting head and face injury propensity simultaneously. The second parameter represents the common correlation between the spine and lower extremity severity propensity. Finally, in terms of exogenous variables, we find that head-on crash associated forward impact significantly

influences face and thorax body regions together. The result indicates that correlation across body region propensities can vary by crash characteristics.

5 POST-ESTIMATION EXERCISES

The model estimation is augmented with a set of post-estimation exercises including validation, illustrative policy scenario analysis and elasticity effects. In the validation exercise, the performance of the estimated model in prediction is evaluated using a hold-out sample (records not used in estimation). The policy scenario analysis conducts an examination of how the proposed model predicts changes in severity outcomes in response to changes to the independent variables. Finally, as the parameters of the exogenous variables in Table 1 do not directly provide the magnitude of their impact body region specific driver injury severity, we undertake an elasticity computation exercise to present the magnitude of the impacts (see Kabli et al., 2020; Eluru and Bhat, 2007 for a similar procedure).

5.1 Validation Analysis

A validation exercise using a holdout sample is carried out to evaluate the predictive performance of the estimated model. For this validation exercise, different records (see section 3) from each year are randomly selected from the unused data resulting in a hold-out sample with 15,141 records. The comparison results between our actual shares (observed) and the predicted sample are shown in Table 2. These comparison samples contain the average values for all five cohorts. We can conclude that the holdout sample results are comparable to the actual shares, suggesting a reasonable fit of the proposed model to holdout sample and the absence of overfitting.

5.2 Policy Analysis

From the MSRPGOP model results, it is not possible to identify the magnitude of the impact of the variables on body region specific injury severity propensity due to the non-linear interaction of variables in propensity, thresholds, and scale components. Therefore, to provide a better understanding of the impacts of independent variables, we compute disaggregate level variations in body region specific injury severity levels. In particular, we generated a host of hypothetical scenarios considering significant exogenous attributes from the final model specification.

We consider a driver involved in a forward impact crash that occurred on an undivided road, with a steering wheel airbag deployment. For the hypothetical condition, we generate the probability profile for a male senior driver over the 12-year period while changing other attributes to better understand the temporal variation on injury severity profile across the body regions. A total of seven hypothetical scenarios for all body regions are considered as follows:

1. Driver condition (1): Male Senior driver not wearing a seatbelt, driving a Light truck which is more than 3-years-old, and involved in head-on crash, driving in dark road with speed limit ≥ 50mph.
2. Driver condition (2): Male Senior driver not wearing a seatbelt, driving a Light truck which is less than 3-years-old, and involved in head-on crash, driving in dark road with speed limit ≥ 50mph.
3. Driver condition (3): Male Senior driver not wearing a seatbelt, driving a Light truck which is less than 3-years-old, and involved in head-on crash, driving in daylight road with speed limit ≥ 50mph.
4. Driver condition (4): Male Senior driver wearing a seatbelt, driving a Light truck which is less than 3-years-old, and involved in head-on crash, driving in daylight road with speed limit ≥ 50mph.

5. Driver condition (5): Male Senior driver wearing a seatbelt, driving a Utility vehicle which is less than 3-years-old, and involved in head-on crash, driving in daylight road with speed limit ≥ 50mph.
6. Driver condition (6): Male Senior driver wearing a seatbelt, driving a Utility vehicle which is less than 3-years-old, and involved in rear-end crash, driving in daylight road with speed limit ≥ 50mph.
7. Driver condition (7): Male Senior driver wearing a seatbelt, driving a Utility vehicle which is less than 3-years-old, and involved in rear-end crash, driving in daylight road with speed limit < 50mph.

The MSRPGOP model is employed to generate the probability of the model prediction under these scenarios for all the five time cohorts considered in the analysis (2003,2006, 2009, 2012 and 2015). The reader would note that the probability plots provided are only a sample of the various illustrations that can be generated based on the independent variables in the models. The results presented in Figure 4, are represented using a heatmap classified into three injury severity levels (except for neck). The probability in the heatmap is scaled from 0 to 1 using a color gradient ranging from dark blue color to red color. The ensuing discussion is focused on the two severe alternatives of severity for the sake of brevity.

Several observations can be made from Figure 4. *First*, from the heatmap we can observe that probabilities of injury severity levels vary significantly by body regions for the considered hypothetical scenarios. The results provide support to the need to consider disaggregate body region specific severity analysis. *Second*, the results presented in Figure 4, in general, offer support to the variable trends described in the model results. *Third*, for driver condition (1), thorax and lower extremity regions are under higher risk in both minor and moderate severity level while face and upper extremity region have the highest probability for minor severity. Furthermore, risk of injury is lowering over the years for most body regions except for abdomen and extremity regions. These results warrant a consideration from vehicle manufacturers on potential design modifications over the years that might have resulted in this trend. *Fourth*, the risk of severe injury decreases significantly when wearing a seat belt (change from driving condition (3)–(4)). *Fifth*, driver condition change (4)–(5) indicates an increase in injury risk across all body regions (except neck and spine) highlighting how light trucks are likely to be safer relative to utility vehicles. *Finally*, the probability plots produced unequivocally demonstrate that the safety trends of driver body regions have changed over time. The development of such injury severity profiles could assist decision makers, vehicle manufacturers, and transportation officials in developing recommendations and potential solutions for improving driver safety.

5.3 Elasticity Effects

Given the expansive information generated from our elasticity exercises, it is not feasible to present everything in the paper. Hence, we select only a subset of information focused on elasticity analysis for discussion in the paper. The reader is invited to review the complete elasticity analysis in the Supplementary Materials document.

For presenting elasticity effects, we examine the evolving relationship between vehicle type (automobile, utility vehicle and light truck), crash type (roadside departure, forward impact, backward impact, driver side impact, forward impact - head on and forward impact - rear end), and vehicle age (less than or equal to 3 years and greater than 3 years) on crash severity for Head and Thorax. The results for these elasticity effects are presented in Tables 3 and 4. The elasticity effects presented illustrate the percentage change in severity levels for each body region for the corresponding vehicle type, age and crash type combination. From Table 3, we can observe that for drivers of Utility vehicles and Light Trucks (compared to drivers of automobiles) irrespective of crash type are likely to be involved in less severe

outcomes. The result is further substantiated by more detailed analysis in Table 4. In this table, we evaluate if the vehicle age affects the results of severity outcome. As expected, newer vehicles offer improved safety outcomes. However, it is interesting to note that the drop in safety levels from newer to older vehicles is reasonably smaller indicating that the vehicle type dimension affects safety more than vehicle age. The finding while intuitive should have significant bearing on vehicle purchase decisions for consumers. Under similar crash conditions, utility vehicles and light trucks offer substantially less severe severity outcomes in the event of a crash. Among utility vehicles and light trucks, higher level of safety is offered by light trucks. While the magnitude of impact might vary by crash type (such as roadside departure and forward impact) and body region (Head and Thorax), the sign of the impact is still consistent across these data. The analysis presented is an illustration of the complex multivariate analysis that can be conducted while controlling for all other attributes.

6 CONCLUSION

In this study, we build on our earlier work (Kabli et al., 2020) to incorporate the influence of temporal factors on parameters influencing body region specific severity. To elaborate, we adapt the recently proposed multivariate body region specific model to accommodate for temporal factors – observed and unobserved – on body region specific injury severity. For this purpose, we adopt a hybrid approach that accommodates for the unobserved factors using two mechanisms. First, we parameterize unobserved temporal factor variation through the customization of the variance by time cohort (heteroscedasticity). Second, the common unobserved factors affecting severity across various body regions is accommodated through traditional random parameter consideration process. The proposed model was developed using data sourced from the National Automotive Sampling System-Crashworthiness Data System (NASS-CDS) database for the time cohorts 2003, 2006, 2009, 2012, and 2015. The model development was accomplished through the use of a variety of independent variables including driver characteristics, vehicle characteristics, crash characteristics, roadway characteristics, environmental characteristics, and temporal variables. The empirical analysis involves the estimation of three different model systems for driver severity for the eight body regions: 1) a set of Independent Scaled Ordered Probit models (ISOP), 2) a set of Independent Scaled Generalized Ordered Probit Models (ISGOP) and 3) Multivariate Scaled Random Parameters Generalized Ordered Probit model (MSRPGOP). The comparison exercise, based on the BIC value, clearly highlights the superiority of the MSRPGOP model over other models. The final model estimates clearly illustrates the varying impact of several variables (both in sign and magnitude) on the injury severity level across body regions. We found that our proposed model clearly illustrates the effect of temporal factors (measured as time elapsed variable) from 2003 has an observed impact on severity and also has an unobserved effect in the form of heteroscedasticity by resulting in an altered severity propensity variance across cohorts. With respect to random parameters, we find the presence of three common unobserved factors from our analysis.

The model estimation results are supplemented by hold-out sample validation, illustrative policy scenario analysis and comprehensive elasticity effects computation. The results of the elasticity exercise evaluating the influence of crash type, vehicle type, vehicle age for Head and Thorax regions illustrate the influence of vehicle type on crash severity outcomes. The results also indicate the role of vehicle age in reducing severity (Kim et al., 2013; Khattak, 2001).

The research exercise also demonstrates the benefit of employing an ordered model system for modeling injury severity. An unordered model framework application for 8 body regions would be substantially more cumbersome resulting in an explosion of potential

unobserved factors to be considered in model estimation with little to no gain in model explanation power. We think that as we move towards body region specific injury severity analysis, it becomes imperative that we employ an ordered outcome model framework for severity analysis.

Further, the proposed approach offers an alternative framework for accommodating temporal effects over long time horizons. In safety literature, three approaches have been employed to determine temporal instability. In the first approach, model is estimated using the full data (all time periods) and then compared with year-specific models using an appropriate likelihood-ratio test (see Tamakloe et al., 2020; Islam and Mannering, 2020; Islam and Mannering, 2021). A second approach employs a "pairwise" test to investigate the temporal instability between any two years by examining whether the parameters estimated from one subgroup are statistically different from another (see Al-Bdairi et al., 2020; Alnawmasi and Mannering, 2019; Behnood and Mannering, 2015; Behnood and Mannering, 2019; Hou et al., 2020; Islam et al., 2020; Li et al., 2021; Se et al., 2021; Tamakloe et al., 2021; Yan et al., 2021; Yu et al., 2021; Zubaidi et al., 2021; Hou et al., 2022). Finally, the approach employed in our paper serves as the third approach. In studies with long time horizons, our proposed approach offers advantages in terms of parsimony and prediction. To elaborate, while the year specific models are temporally resilient, the approach does not provide any process for predicting into the future. With increasing adoption of temporal stability in models, it is worth considering a comparison across these methods in a single study.

To be sure, the paper is not without limitations. In our study, we focused on injury severity for drivers over time. Any attempt to consider multiple occupants will increase the order of the dependent variables substantially (at the rate of 8 per additional occupant). Further, the reader would note that considering an unbiased sample (as available in NASS-CDS), resulted in a low percentage of severe injury data sample potentially resulting in a very restrictive model specification for severe injury categories.

CONFLICT OF INTEREST

There is no conflict of interest.

ACKNOWLEDGMENTS

The authors would like to gratefully acknowledge the National Highway Traffic Safety Administration for providing access to National Automotive Sampling System-Crashworthiness Data System (NASS-CDS) database**.**

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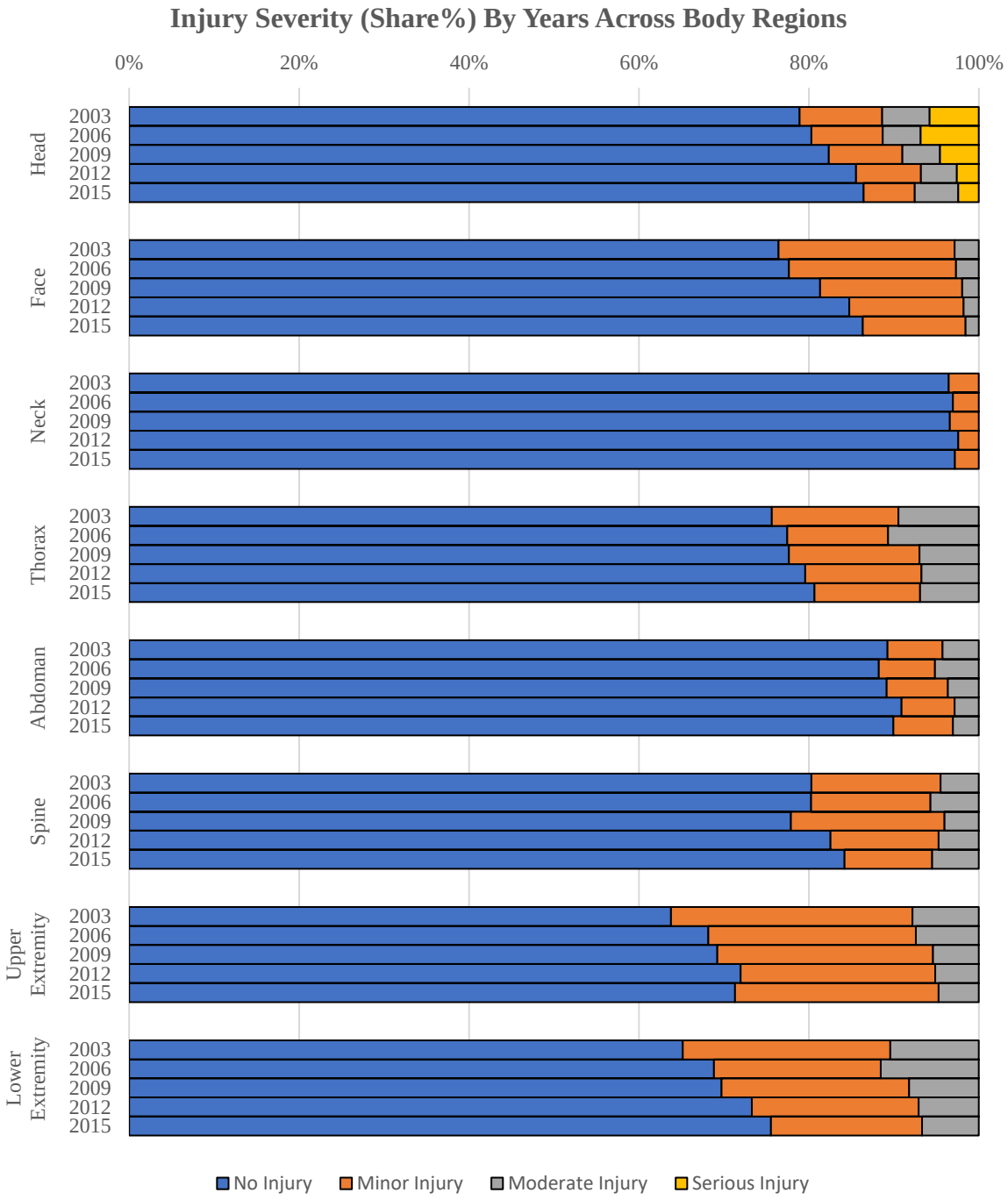

FIGURE 1 Distribution of The Random Sample Size for The Driver Injury Severity Levels by Body Region Over Time

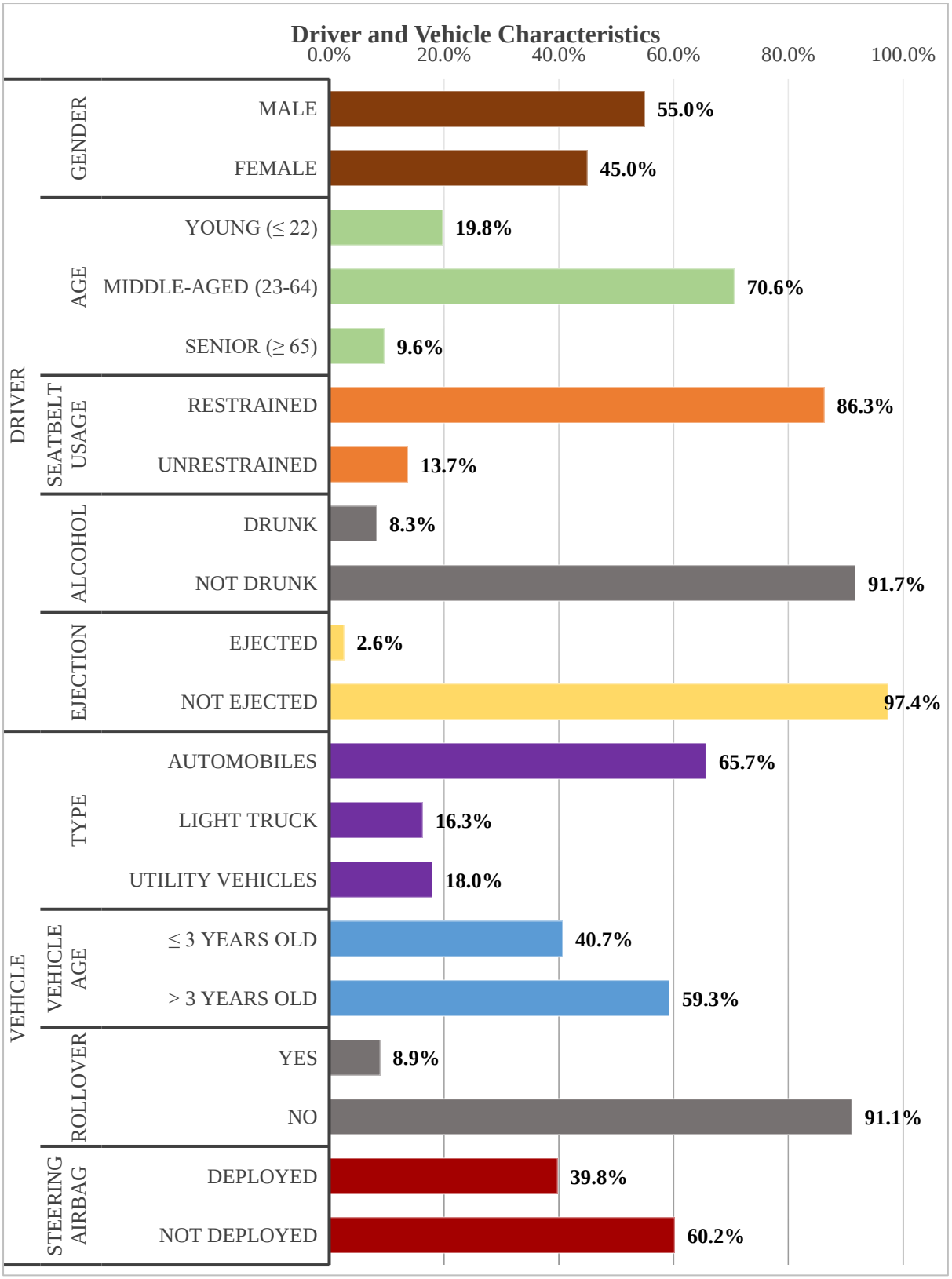

FIGURE 2 Sample Characteristics (Driver and Vehicle Related Factors).

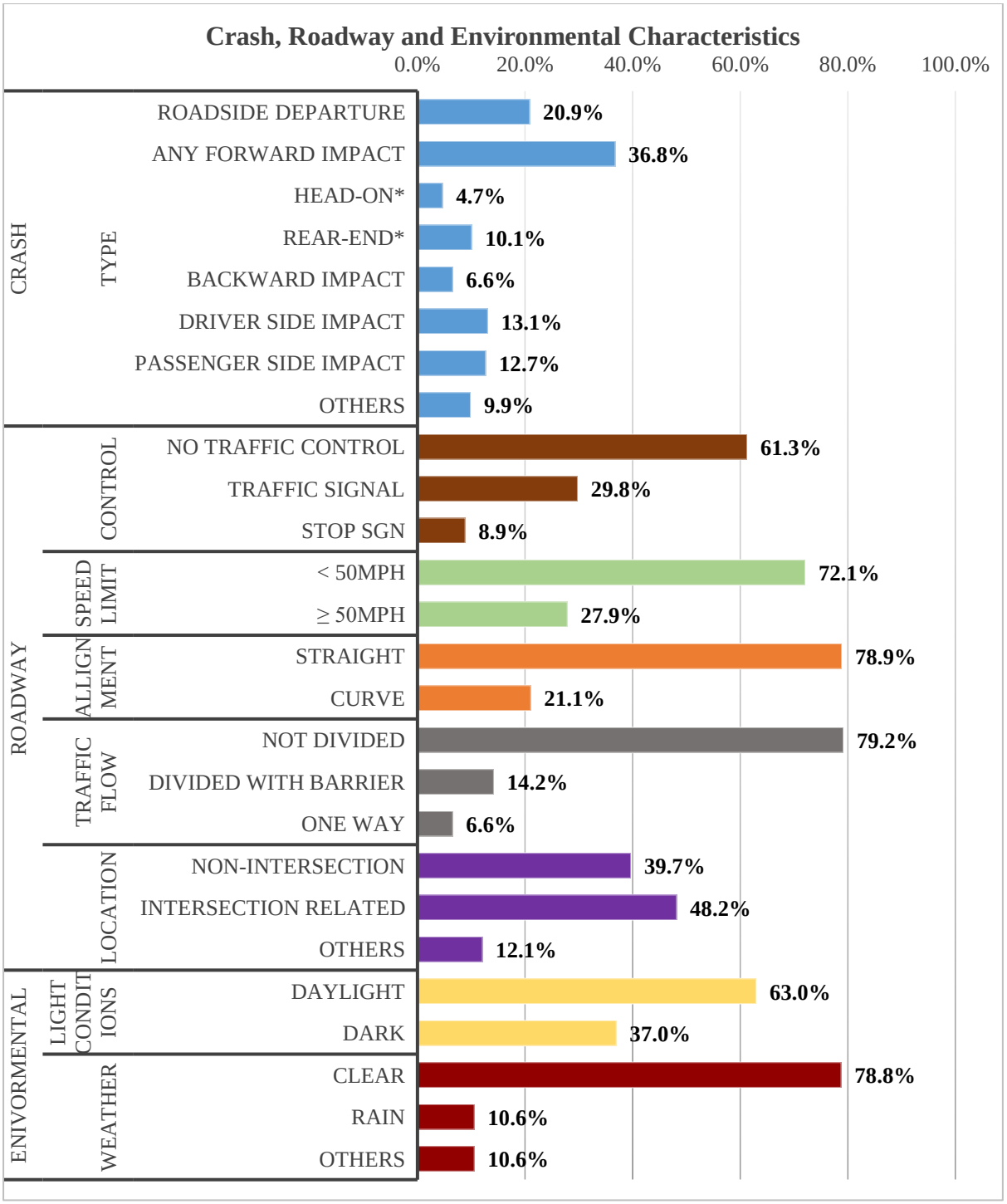

FIGURE 3 Sample Characteristics (Crash, Roadway and Environment Related Factors).

* Head on and Rear-end crashes are part of the Any Forward Impact crash type (interaction terms).

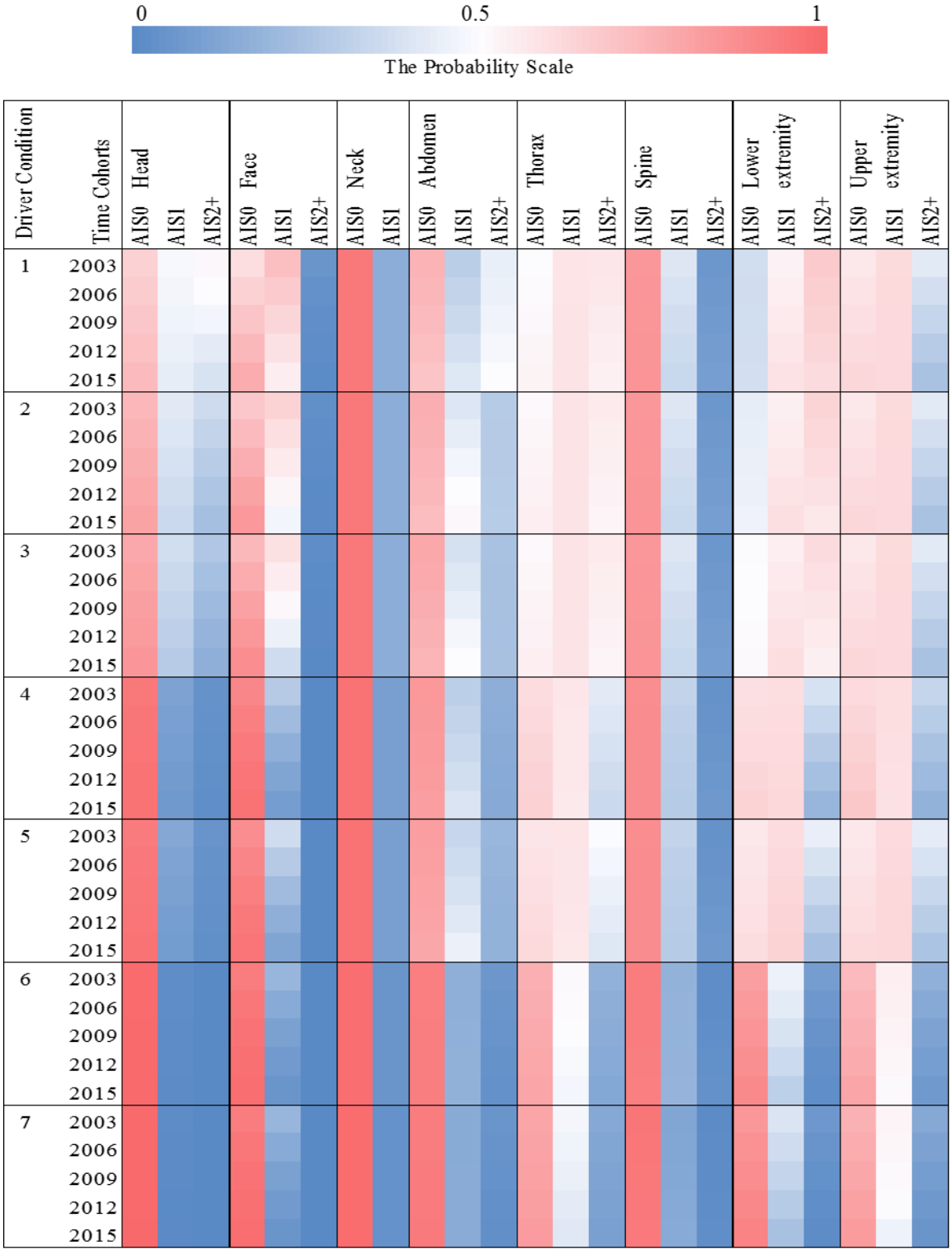

FIGURE 4 Probability Plots of Driver Injury Severity Profiles across Different Years for Hypothetical Scenarios.

(AIS0= No Injury, AIS1= Minor Injury, AIS2+= Moderate Injury and Higher)

TABLE 1 Multivariate Scaled Random Parameters Generalized Ordered Probit Model Results.

Variables Name	BODY REGIONS							
	Head	*Face*	*Neck*	*Abdomen*	*Thorax*	*Spine*	*Lower extremity*	*Upper extremity*
	Coefficient (T-stat)	Coefficient (T-stat)	Coefficient (T-stat)	Coefficient (T-stat)	Coefficient (T-stat)	Coefficient (T-stat)	Coefficient (T-stat)	Coefficient (T-stat)
Threshold Parameters								
Threshold 1	1.742 (20.450)	1.320 (15.431)	2.206 (33.367)	1.379 (21.860)	0.837 (14.351)	1.060 (17.938)	0.715 (13.717)	0.745 (16.515)
Threshold 2	-0.244 (-4.725)	0.565 (12.644)	---	-0.822 (-11.099)	-0.486 (-12.710)	0.156 (3.447)	0.109 (2.515)	0.138 (3.260)
Threshold 3	-0.293 (-4.632)	---	---	---	---	---	---	---
Temporal variables								
Time elapsed (linear)	-0.023 (-3.483)	-0.054 (-5.958)	---[1]	0.020 (2.103)	-0.012 (-3.010)	-0.023 (-2.671)	-0.015 (-2.493)	-0.019 (-2.589)
Driver Characteristics								
Younger driver (Middle-aged is base)	---	---	---	-0.104 (-2.084)	-0.170 (-3.702)	---	---	---
Senior driver (Middle-aged is base)	---	0.228 (2.593)	---	0.156 (2.710)	0.457 (8.459)	0.169 (2.168)	0.153 (2.534)	0.213 (4.301)
Male (Female is base)	---	---	-0.265 (-4.219)	-0.167 (-4.380)	-0.175 (-4.979)	-0.265 (-5.878)	-0.306 (-7.958)	-0.172 (-5.452)
Drunk (Not drunk is base)	0.345 (3.718)	0.497 (5.310)	---	---	---	---	---	---
Unrestrained (Restrained is Base)	0.965 (12.749)	0.810 (10.539)	0.257 (3.097)	0.247 (4.584)	0.395 (7.574)	0.189 (2.698)	0.419 (7.386)	0.169 (3.526)
Between minor and moderate injury	---	---	---	---	---	---	-0.249 (-3.901)	---
Vehicle Characteristics								
Vehicle age $\leq$ 3 years old ($>$ 3 years old is base)	-0.335 (-5.729)	-0.286 (-4.958)	---	-0.066 (-1.706)	-0.058 (-1.681)	---	-0.122 (-3.354)	---
Between minor and moderate injury	---	---	---	0.427 (4.752)	---	---	---	---

Utility vehicle (base is Automobile car)	-0.117 (-1.716)	---	---	---	-0.087 (-1.902)	---	---	---
Light truck (pickup, van) (base is Automobile car)	-0.200 (-2.546)	-0.160 (-2.095)	---	-0.104 (-1.909)	-0.204 (-3.969)	---	-0.104 (-2.089)	-0.189 (-4.377)
Rollover	0.630 (6.786)	0.436 (4.718)	0.208 (1.991)	0.129 (1.989)	0.232 (3.625)	0.316 (3.981)	0.145 (2.274)	0.467 (7.937)
Between minor and moderate injury	---	---	---	---	---	-0.416 (-4.421)	---	---
Driver ejected	1.296 (8.894)	0.652 (4.150)	0.693 (1.991)	0.796 (7.958)	0.837 (7.700)	0.866 (6.339)	0.610 (5.851)	0.851 (8.356)
Steering air bag deployed	0.446 (7.264)	0.529 (5.759)	0.388 (6.031)	0.406 (9.336)	0.505 (14.077)	0.197 (4.117)	0.742 (16.701)	0.497 (9.110)
Between minor and moderate injury	-0.200 (-2.595)	0.220 (3.944)	---	---	---	---	---	---
Steering airbag deployed* time elapsed (linear)	---	0.037 (3.010)	---	---	---	---	---	0.018 (2.502)
Crash Characteristics								
Roadside departure (base is passenger side and other)	0.174 (2.316)	---	---	---	---	---	0.130 (2.570)	0.171 (3.116)
Standard deviation	---	---	---	---	---	---	---	0.367 (2.301)
Any forward impact	-0.506 (-5.862)	-0.445 (-6.773)	---	-0.244 (-5.404)	-0.156 (-3.349)	-0.158 (-2.892)	-0.218 (-4.539)	---
Between minor and moderate injury	---	---	---	---	0.481 (7.982)	---	---	---
Head On	0.684 (5.173)	0.394 (2.755)	0.287 (2.262)	0.597 (6.926)	0.537 (5.590)	---	0.696 (7.295)	0.456 (6.541)
Rear end	-0.283 (-2.354)	---	---	---	-0.149 (-2.065)	-0.389 (-4.075)	-0.264 (-3.541)	-0.140 (-2.655)
Backward impact	---	-0.256 (-2.171)	---	-0.171 (-1.962)	-0.311 (-3.776)	0.478 (5.986)	-0.217 (-2.727)	---
Driver side impact	0.424 (5.159)	---	0.317 (3.672)	---	---	---	---	0.205 (4.284)
Between minor and moderate injury	---	---	---	---	---	---	---	-0.149 (-2.201)

Roadway Characteristics								
Speed limit ≥ 50mph (< 50mph is base)	0.223 (3.722)	---	0.127 (1.703)	0.083 (1.858)	0.137 (3.023)	0.207 (3.642)	0.125 (2.764)	0.125 (3.540)
Between moderate and serious injury	-0.240 (-2.149)	---	---	---	---	---	---	---
Divided with barrier (Not divided is based)	---	---	0.178 (1.982)	---	-0.107 (-1.860)	-0.225 (-2.976)	-0.104 (-1.779)	---
One way	---	-0.194 (-1.841)	---	---	---	-0.183 (-1.920)	---	-0.118 (-1.892)
Curved road (straight is base)	---	---	0.153 (2.139)	0.107 (2.364)	0.099 (2.343)	0.165 (3.065)	---	---
Stop sign (traffic control and no control are based)	---	---	---	0.158 (2.430)	---	---	---	0.103 (1.964)
Intersection related (non-intersection is base)	---	-0.352 (-6.308)	---	-0.081 (-1.860)	-0.083 (-2.045)	---	---	---
Environmental Characteristics								
Dark (base is daylight)	0.197 (3.324)	0.191 (3.242)	---	0.087 (2.210)	---	---	0.098 (2.619)	---
Rain	-0.171 (-1.996)	---	---	-0.108 (-1.720)	-0.108 (-1.901)	---	---	---
Scale parameter								
linear	---	---	---	-0.021 (-2.584)	---	0.021 (3.361)	-0.018 (-2.337)	-0.010 (-1.799)
Correlation								
Correlation 1 (Head and Face)			1.162 (26.835)					
Correlation 2 (Spine and Lower extremity)			0.640 (17.555)					
Head On (Face and Thorax)			0.891 (10.417)					

[1] ---= attribute insignificant at 90% significance level

TABLE 2 Aggregate Measures for Actual shares and Validation Sample

Injury Severity Level	BODY REGIONS															
	Head		*Face*		*Neck*		*Abdomen*		*Thorax*		*Spine*		*Lower extremity*		*Upper extremity*	
	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.	Obs.	Pred.
No injury	81.30	83.85	79.33	85.77	96.42	95.67	89.57	87.42	77.29	72.88	80.41	78.32	69.36	67.06	67.68	60.59
Minor injury	9.15	8.94	18.28	13.64	3.58	4.33	6.74	7.44	14.47	16.38	14.54	17.32	21.31	24.36	25.75	29.75
Moderate injury	4.50	3.72	2.39	0.59	---	---	3.69	5.13	8.24	10.74	5.05	4.35	9.33	8.59	6.56	9.66
Serious injury	5.05	3.48	---	---	---	---	---	---	---	---	---	---	---	---	---	---

TABLE 3 The Elasticity Effects Between Vehicle Types and Across All Crash Types by Body Region

Body Region	Vehicle Type	Injury Severity Level	Roadside departure	Any forward impact	Backward impact	Driver side impact	Head On	Rear end
Head	Utility vehicle	No Injury	3.05	0.82	---	2.15	2.73	0.39
		Minor Injury	-9.15	-16.35	---	-14.40	-12.09	-19.96
		Moderate Injury	-11.30	-18.79	---	-17.13	-16.21	-20.76
		Serious Injury	-14.17	-21.99	---	-18.24	-21.10	-23.12
	Light truck	No Injury	5.09	1.35	---	3.54	4.55	0.64
		Minor Injury	-15.42	-27.03	---	-23.72	-20.33	-32.93
		Moderate Injury	-18.83	-30.86	---	-28.01	-26.92	-34.64
		Serious Injury	-23.45	-35.83	---	-30.40	-34.38	-36.31
Thorax	Utility vehicle	No Injury	---	2.75	1.71	---	5.57	2.12
		Minor Injury	---	-9.26	-12.03	---	-5.05	-11.32
		Moderate Injury	---	-15.68	-17.37	---	-12.82	-18.10
	Light truck	No Injury	---	6.24	3.78	---	12.97	4.75
		Minor Injury	---	-21.35	-27.14	---	-12.21	-25.72
		Moderate Injury	---	-34.55	-37.44	---	-28.86	-39.09

TABLE 4 The Elasticity Effects for Head and Thorax Between Vehicle Types and Across All Crash Types by Vehicle Age

Body region	Vehicle type	Injury Severity Level	Roadside departure		Any forward impact		Backward impact		Driver side impact		Head On		Rear end	
			≤ 3 years	> 3 years	≤ 3 years	> 3 years	≤ 3 years	> 3 years	≤ 3 years	> 3 years	≤ 3 years	> 3 years	≤ 3 years	> 3 years
Head	Utility vehicle	No injury	2.16	3.60	0.51	1.04	---	---	1.51	2.72	1.71	3.24	0.26	0.49
		Minor injury	-11.98	-8.20	-19.78	-15.25	---	---	-17.62	-13.01	-16.03	-11.18	-22.04	-19.19
		Moderate injury	-14.12	-10.53	-23.09	-17.76	---	---	-21.56	-15.78	-20.79	-15.40	-22.89	-20.05
		Serious injury	-16.43	-13.72	-27.59	-21.23	---	---	-22.96	-17.39	-26.81	-20.51	-25.57	-22.57
	Light truck	No injury	3.59	6.03	0.83	1.73	---	---	2.43	4.52	2.82	5.42	0.42	0.82
		Minor injury	-19.83	-13.94	-32.09	-25.41	---	---	-28.59	-21.62	-26.50	-18.90	-35.42	-32.01
		Moderate injury	-23.40	-17.59	-37.18	-29.34	---	---	-34.27	-26.11	-34.07	-25.65	-37.07	-33.83
		Serious injury	-27.53	-22.64	-44.41	-34.66	---	---	-36.85	-29.23	-44.38	-33.37	-41.99	-35.05
Thorax	Utility vehicle	No injury	---	---	2.71	2.77	1.60	1.78	---	---	5.55	5.58	2.16	2.09
		Minor injury	---	---	-9.63	-9.01	-12.57	-11.70	---	---	-5.36	-4.90	-11.27	-11.36
		Moderate injury	---	---	-16.39	-15.25	-18.16	-16.95	---	---	-13.45	-12.58	-18.06	-18.13
	Light truck	No injury	---	---	6.10	6.35	3.51	3.96	---	---	12.86	13.02	4.80	4.72
		Minor injury	---	---	-22.03	-20.90	-28.08	-26.57	---	---	-12.83	-11.93	-25.42	-25.96
		Moderate injury	---	---	-35.60	-33.92	-38.34	-36.95	---	---	-30.17	-28.34	-38.55	-39.52