Examining Correlations Between Motorcyclist's Conspicuity, Apparel Related Factors and Injury Severity Score: Evidence from New Motorcycle Crash Causation Study

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CITATION: Wali, B., Khattak, A. J., & Ahmad, N. (2019). Examining correlations between motorcyclist's conspicuity, apparel related factors and injury severity score: Evidence from new motorcycle crash causation study. *Accident Analysis & Prevention*, *131*, 45-62.

February 3rd, 2019

Accepted for Publication in:
Accident Analysis and Prevention

Examining Correlations Between Motorcyclist's Conspicuity, Apparel Related Factors and Injury Severity Score: Evidence from New Motorcycle Crash Causation Study

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Abstract – Motorcyclists are vulnerable road users at a particularly high risk of serious injury or death when involved in a crash. In order to evaluate key risk factors in motorcycle crashes, this study quantifies how different "policy-sensitive" factors correlate with injury severity, while controlling for rider and crash specific factors as well as other observed/unobserved factors. The study analyzes data from 321 motorcycle injury crashes from a comprehensive US DOT FHWA's Motorcycle Crash Causation Study (MCCS). These were all non-fatal injury crashes that are representative of the vast majority (82%) of motorcycle crashes. An anatomical injury severity scoring system, termed as Injury Severity Score (ISS), is analyzed providing an overall score by accounting for the possibility of multiple injuries to different body parts of a rider. An ISS ranges from 1 to 75, averaging at 10.32 for this sample (above 9 is considered serious injury), with a spike at 1 (very minor injury). Preliminary cross-tabulation analysis mapped ISS to the Abbreviated Injury Scale (AIS) injury classification and examined the strength of associations between the two. While the study finds a strong correlation between AIS and ISS classification (Kendall's tau of 0.911), significant contrasts are observed in that, when compared to ISS, AIS tends to underestimate the severity of an injury sustained by a rider. For modeling, fixed and random parameter Tobit modeling frameworks were used in a corner-solution setting to account for the left-tail spike in the distribution of ISS and to account for unobserved heterogeneity. The developed random parameters Tobit framework additionally accounts for the interactive effects of key risk factors, allowing for possible correlations among random parameters. A correlated random parameter Tobit model significantly out-performed the uncorrelated random parameter Tobit and fixed parameter Tobit models. While controlling for various other factors, we found that motorcycle-specific shoes and retroreflective upper body clothing correlate with lower ISS on-average by 5.94 and 1.88 units respectively. Riders with only partial helmet coverage on-average sustained more severe injuries, whereas, riders with acceptable helmet fit had lower ISS Methodologically, not only do the individual effects of several key risk factors vary significantly across observations in the form of random parameters, but the interactions between unobserved factors characterizing random parameters significantly influence the injury severity score as well. The implications of the findings are discussed.

Keywords: Motorcycle crash causation, injury severity score, correlated and uncorrelated random parameters, Tobit model, conspicuity and apparel.

1. INTRODUCTION & BACKGROUND

Compared to passenger vehicles, motorcycles are less stable and less visible (i.e., higher susceptibility to go undetected). When a motorcycle crashes, the riders lack the protection of an enclosed vehicle and are thus more likely to sustain injuries or fatalities. When controlled for exposure (as per mile traveled in 2015), the number of motorcycle fatalities is nearly 29 times the number of passenger vehicle fatalities (NHTSA 2016). Furthermore, statistics suggest a significant increase in motorcycle fatalities over recent years, i.e., from 3,365 fatalities in 2002 to 4,976 fatalities in 2015 - a 48 percent increase (NHTSA 2016). Owing to this alarming concern, the U.S. Congress, through the Safe, Accountable, Flexible, and Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU), recently directed the U.S.

Department of Transportation to conduct a comprehensive study aimed at identifying the causes of motorcycle crashes (NHTSA 2017). Subsequently, the U.S. Federal Highway Administration initiated a comprehensive research effort called the Motorcycle Crash Causation Study (MCCS), targeted at identifying causes of motorcycle crashes (NHTSA 2017, Wali et al. 2018e).

While there has been considerable research work on motorcycle safety in previous decades (Hewson 2004, Rolison et al. 2013, Araujo et al. 2017), motorcycle safety remains a significant concern. The motorcycle research arena provides different prevailing safety analysis themes (Araujo et al. 2017). The extensive body of the literature has focused on analyzing the frequency of motorcycle crashes at specific roadway locations, such as segments or intersections (Hewson 2004, Haque et al. 2010, Schneider IV et al. 2010, Haque et al. 2012, Rolison et al. 2013, Gabauer and Li 2015). By focusing on motorcycle crash occurrence, the key focus of such studies is to examine how different roadway geometric, environmental, and traffic related factors relate to motorcycle crash frequency at roadway segments or intersections (Haque et al. 2010, Schneider IV et al. 2010, Haque et al. 2012, Gabauer and Li 2015). This type of analysis is useful in that it helps develop motorcycle-specific safety performance functions for certain roadway locations (Chin and Quddus 2003, Schneider IV et al. 2010). However, such an analysis does not provide information on how different policy-sensitive factors relate to injury outcomes in motorcycle crashes.

In this regard, a broad spectrum of studies have focused on analyzing the relationships between different factors and injury severity outcomes/injury crash propensity, given a crash (Quddus et al. 2002, Savolainen and Mannering 2007, Shaheed et al. 2013, Chung et al. 2014, Cheng et al. 2017, Islam and Brown 2017, Wali et al. 2018e). Given a crash, the focus is to investigate how a confluence of factors may contribute to an injury severity outcome (such as no injury vs. fatal injury). In order to link motorcyclist’s injury outcomes with explanatory factors, researchers typically use discrete outcome models such as multinomial logit (Shankar and Mannering 1996), nested logit (Savolainen and Mannering 2007), mixed logit (Shaheed et al. 2013), ordered probit models (Quddus et al. 2002, Blackman and Haworth 2013), and correlated random parameters count or ordered approaches (Fountas and Anastasopoulos 2018, Fountas et al. 2018a, Hou et al. 2018). Collectively, a variety of crash contributory factors such as rider-related factors (Schneider et al. 2012), roadway geometrics (Quddus et al. 2002, Haque et al. 2010), motorcycle characteristics (Savolainen and Mannering 2007), and environmental factors (Rifaat et al. 2012) are associated with motorcycle crash outcomes (Quddus et al. 2002, Savolainen and Mannering 2007, Shaheed et al. 2013, Chung et al. 2014, Cheng et al. 2017, Islam and Brown 2017).

In special relevance to the current study, a recent study by Wali et al. (2018) conducted a heterogeneity-based matched case control analysis of the MCCS data in order to quantify the relative risks of different “policy-sensitive” key risk factors on injury crash propensity (Wali et al. 2018e). Overall, to reduce injury crash propensity, the study indicated the need to develop appropriate countermeasures such as refresher training courses for riders, preventing sleep-deprived/fatigued riding, and preventing riding under the influence of alcohol and drugs (Wali et al. 2018e). Along these lines, Goodwin et al. (2015) provides comprehensive guidance for selecting effective, evidence-based countermeasures that improve motorcycle safety (Goodwin et al. 2015). Safety practitioners can use the findings from these studies to develop different crash, roadway, and environment-specific countermeasures that can help reduce motorcycle injury outcomes in crashes (Goodwin et al. 2015).

All the aforementioned studies (and the references therein) have provided valuable insights. However, owing to the lack of more comprehensive motorcycle crash data, several important gaps remain. First, the majority of the motorcycle injury severity literature is based on data from traditional police crash reports (Quddus et al. 2002, Savolainen and Mannering 2007, Islam and Brown 2017). An earlier study that used comprehensive MCCS database did not look explicitly into crash injury outcomes (Wali et al. 2018e). Police-reported crash data typically classifies motorcycle rider injury severity into only four types: fatal injury, major injury, minor injury, and possible/no injury (Savolainen and Mannering 2007, Islam and Brown 2017). Also, the police-reported injury severity information does not typically account for the possibility of multiple injuries to different body parts of a rider. For example, a crash where a motorcycle rider sustains a major injury to the head and a crash in which a rider sustains one major injury to the head and another to the chest will both be classified as a major injury crash in police crash data even though the latter is more severe than the former. Even though most motorcycle crashes involve injuries to more than one body part, the safety literature does not use scales for describing multiply injured riders. Second, information on several of the important factors believed to be correlated with rider injury outcomes may not be available in traditional police reported crash data or, if available, are subject to considerable bias. For example, it is very difficult for the reporting police officer to determine the motorcycle speed before a crash or if the rider was fatigued or apparently asleep unless the crash is scientifically reconstructed. Likewise, police reported crash data typically does not provide information on rider experience, apparel type, conspicuity, type and coverage of the helmet, and socio-demographics (to name a few) (Shaheed et al. 2013, Wali et al. 2018e), all of which are "high-priority" key risk factors in the U.S. DOT's National Agenda for Motorcycle Safety (NHTSA 2013).

Given these prevalent gaps in the literature, the key objectives of the present study are to: (1) investigate how rider experience, apparel type and conspicuity relate to motorcycle injury severity outcomes, (2) quantify the relationships between helmet type and coverage, rider-specific characteristics (alcohol and drug intake, rider age, physical impairment, etc.) and injury severity outcomes, and to (3) fully account for uncorrelated and correlated unobserved heterogeneity in a corner-solution empirical framework. Compared to analysis based on traditional police-reported crashes through injury severity measures such as KABCO and/or the Abbreviated Injury Scale (AIS), the present study takes a unique approach by analyzing an anatomical injury severity scoring system, the Injury Severity Score (ISS), that provides an overall score by accounting for the possibility of multiple injuries to different body parts of a rider in a crash. Using data from the most comprehensive Motorcycle Crash Causation Study, information on injury severity is linked with detailed crash-specific, environmental, helmet, motorcycle rider, and contributory factors related data. Methodologically, owing to the corner-solution nature of ISS (discussed in detail in Section 2.3), we use a Tobit modeling framework. Related to objective 3, issues related to unobserved heterogeneity should be fully accounted for in order to reach reliable conclusions (Arvin et al. 2019). To this effect, this study employs a fully flexible random parameter Tobit modeling framework which accounts for heterogeneous effects of exogenous factors due to systematic variations in unobserved factors. Compared to the standard random parameter modeling framework, the empirical analysis presented in this paper accounts for uncorrelated as well as correlated unobserved heterogeneity in the effects of exogenous factors on the injury severity score (discussed in detail in section 2.3). That is, in addition to the contours of unobserved heterogeneity, we examine the likely interactive effects of unobserved factors on the injury severity score. In the context under discussion (i.e., injury severity scores), such an extension is crucial given that several determinants of heterogeneity are likely to exhibit mixed or interactive effects on the rider's injury generating mechanisms. To the best of authors' knowledge, the use of such a method has not been used/reported in this context.

2. METHODOLOGY

2.1. Data Source

This study builds upon the Federal Highway Administration (FHWA) Motorcycle Crash Causation Study (MCCS)(FHWA 2017). Importantly, MCCS is the most detailed data collection effort in the United States legislated by the U.S. Congress and sponsored by the U.S. Department of Transportation in more than 30 years (FHWA 2017). The MCCS includes data from actual on-scene investigations of 351 motorcycle injury crashes in Orange County, California. The crash data collection protocol is detailed and sophisticated, and it is impractical to cover all the specific details of the protocol; for parsimony we provide an overview. For details see FHWA (2017). For each of the 351 injury crashes, data are available including pre-crash, crash, and post-crash characteristics of the motorcycle riders and crash sites. The study contains extensively detailed information on environmental factors, traffic characteristics, and roadway features that could have contributed to the crash that gives a fuller picture of the crash causation mechanism (FHWA 2017). The MCCS investigators made direct observations, inspected medical records, and conducted interviews in order to collect data on injury details and human factors such as medical conditions, physical characteristics and fatigue levels, demographics, and rider trip purposes. As mentioned earlier, police-reported crash data can be subjective and vulnerable to bias (Mannering and Bhat 2014, Wali et al. 2018f). As such, to get a more objective description of riders' injuries, the trained investigators interviewed crash-involved motorcycle occupants in order to produce detailed descriptions of all injuries (including minor injuries) (FHWA 2017). Because access to medical information is carefully controlled through the U.S. Federal Health Insurance Portability and Accountability Act (HIPAA), investigators executed signed patient release forms in order to obtain copies of patient injury records, emergency room reports, patient discharge summaries, and medical records from private physicians (if applicable) (FHWA 2017). Importantly, as autopsies are public records in California (which is where the MCCS study was conducted), the medical examiner also provided autopsy reports if applicable. Investigators then examined and encoded these exhaustive sets of records. In short, the injury information provided in MCCS is very detailed and reliable, providing a unique source of publicly available information where we can examine motorcyclist injury outcomes at a deeper level.

The data were collected from 2011-2016 in Orange County, California (Bents et al. 2018, HSIS 2018). The highest percentage of crashes occurred on Saturday (18.2%), followed by Friday (17.9%) and Sunday (15.1%) (Bents et al. 2018). In 240 (68.4%) crashes, the motorcycle had a conflict with one vehicle while in 85 (24.2%) crashes no second party was involved. Referring to the lighting condition, 239 (68.1%) and 86 (24.5%) crashes occurred during the day and night time (i.e., lighted, continuous illumination, or spot illumination), respectively. The MCCS statistics show that the highest percentage of crashes (50.4%) occurred during clear weather conditions. In terms of geometry, approximately equal percentage of crashes occurred on roadway segments (non-junctions) (30.2% of crashes) and four-legged intersections (29.0% of crashes). Referring to the speed limit, 127 (36.2%) and 75 (21.4%) crashes occurred on roadways with speed limits of 41-45 MPH and 36-40 MPH, respectively. Two-way divided roads (i.e., without median barriers) were highly crash prone facilities exhibiting 188 (53.6%) of the crashes. Riders between the ages of 21-30 years old were involved in 136 (38.7%) crashes. Female riders were involved in a relatively much lower percent (4.6%) of the crashes compared to male riders (95.4%). A detailed comparison of the MCCS database with the Fatality Analysis Reporting System (FARS) and the National Automotive Sampling System/General Estimate System (NASS/GES) databases can be found in (Bents et al. 2018).

For this study, we have linked the data in injury forms with detailed data in a 1) contributory factors form, 2) environmental form, 3) helmet form, 4) motorcycle dynamics form, and a 5) motorcycle rider form. Altogether, we compiled and analyzed data on more than 1000 variables related to motorcycle rider, crash and motorcycle characteristics, and environmental and roadway factors. More details are provided below.

2.2. Injury Classification

Different injury classification scales are used to classify injuries sustained by drivers/riders in a crash. In the U.S., the police in several states rate traffic crash injury on a five-point scale known as KABCO, which consists of categories assigned as fatal (K), serious (A), moderate (B), minor (C), and none (O). The majority of the traffic safety literature builds upon traditional police-reported crash data, KABCO scale has been widely used in the injury severity literature (Quddus et al. 2002, Savolainen and Mannering 2007, Schneider IV et al. 2010, Ali et al. 2018, Wali et al. 2018f).

As another injury classification system, Abbreviated Injury Scale (AIS) has also been used in the traffic safety literature. AIS ranks injuries on a scale from 1 to 6, with 1 being Minor, 2 being Moderate, 3 being Serious, 4 being Severe, 5 being Critical, and 6 being Un-survivable (untreatable) injury. While an anatomical scoring system, AIS is not an interval scale in that the difference between moderate and minor (AIS2 and AIS1) is not the same as the difference between critical and Un-survivable injury (AIS5 and AIS4).

The use of KABCO in police crash reports provides a simple and intuitive classification of injuries, however, with significant limitations as well. For example, the injury severity information provided in police reports typically relates to the most severe injury sustained by the rider. In other words, the police-reported injury severity information does not typically account for the possibility of multiple injuries to different body parts of a rider. As mentioned earlier, a police-reported major injury crash with only one major injury is different than a crash where two major injuries are sustained by the rider. Nonetheless, both crashes will be classified as major injury crashes in police crash reports with no sensitivity to the possibility of multiple injuries to a rider. Even though most motorcycle (or motor-vehicle) crashes involve injury to more than one body part, the use of scales for describing multiply injured riders has been lacking.

2.2.1 Injury Severity Score – Multiply Injured Riders

Fortunately, the MCCS provides injury severity information (in KABCO and AIS scales) for each of the nine body parts of a rider (FHWA 2017). The detailed injury data are available for the following nine regions: 1) Head, 2) Face, 3) Neck, 4) Thorax, 5) Abdomen, 6) Spine, 7) Upper Extremity, 8) Lower Extremity, and 9) External and other. For exact definitions of the nine body parts, see (Baker et al. 1974). The availability of detailed injury data for each of the body parts allows quantification of injury severity through the Injury Severity Score, which is an anatomical scoring system that accounts for multiply injured riders (Baker et al. 1974). Compared with the commonly used KABCO or AIS systems, ISS is an established medical scoring system used for assessing trauma severity, and which correlates with mortality, morbidity and hospitalization time after trauma (Baker et al. 1974, Stevenson et al. 2001). The ISS is based upon (see below) the Abbreviated Injury Scale (AIS).

In order to calculate ISS for an injured rider, the body is divided into six ISS body regions as follows, 1) Head or neck (including cervical spine), 2) Face (including the facial skeleton, nose, mouth, eyes, and ears), 3) Chest, 4) Abdomen, 5) Extremities or pelvic girdle, and 6) External (Baker et al. 1974). Finally, to calculate an ISS, we take the highest AIS severity code in each of the three most severely injured ISS body regions (as reported by the trained investigator through on-site investigation and inspection of medical records), square each AIS code and add the three squared numbers to get the ISS score for a multiply injured rider. Mathematically, $ISS = X^2 + Y^2 + Z^2$, where X, Y, and Z are the AIS scores of the three most severely injured ISS body regions (Stevenson et al. 2001). The ISS scores range from 1 to 75. If any of the three AIS scores is 6 (meaning an unsurvivable injury), the ISS is automatically set at 75. As an AIS score of 6 indicates uselessness of further medical care in preserving human life, this may indicate a cessation of further medical care in triage for a rider with a score of 6 in any of the three categories. While the injury severity score approach does not explicitly address the non-interval problem in AIS (since ISS is based on AIS), it attempts to quantify the impact of multiple injuries on mortality. The process of summing of the squares in ISS provides a more accurate approximation to mortality prediction.

2.3. Empirical Approach

This paper examines injury severity sustained by a rider given a motorcycle crash. Specifically, we use the injury severity score (ISS) in this study as an anatomical measure of injury severity sustained by different body parts of a rider. As discussed earlier, ISS ranges from 1 to 75 where the distribution in our case contains left-spike at 1, i.e., a corner solution. While clearly acknowledging that this is not a censoring issue per se (explained below), censored regression models can be employed to solve corner-solution problems[1] (Wooldridge 2010).

Over here, we explicitly differentiate between censoring and corner-solution as both are rarely

[1] As the injury severity sustained by a crash-involved rider is of key interest in this study, the application of empirical techniques is conducted in a univariate setting. That is, a single dependent variable (Injury Severity Score) is modeled as a function of several explanatory factors. Of course with an entirely different focus, an alternative approach in the literature is to simultaneously model injury severities sustained by different individuals (drivers and/or passengers) involved in a same crash (Eluru et al. 2010, Russo et al. 2014, Wali et al. 2018f). Depending on data availability and sample size in future (i.e., injury severity score data on drivers and passengers of other vehicles involved in a collision with a motorcycle), injury severity scores of motorcycle riders and passengers, and/or drivers/passengers of crash-involved vehicles can be simultaneously modeled. In this multivariate case, given the continuous (with left spike) nature of ISS, a multivariate Tobit framework with uncorrelated (correlated) heterogeneity can be a potential methodological alternative. For example, see (Anastasopoulos 2016). We do not consider such an approach in this study given our focus is on injury severity sustained by different body parts of the rider (captured through a single ISS), whereas for application of a multivariate Tobit model, we will need to have multiple ISS outcomes for each of the body parts (and which is conceptually and empirically impossible keeping in view the definition of ISS.)

differentiated in the traffic safety literature. Past studies revealed that crash datasets (mainly crash rates) usually exhibit censoring issues (Anastasopoulos et al. 2008, Anastasopoulos et al. 2012). In the case of crash rate (i.e. continuous data), datasets were usually considered left-censored due to road segments where no crashes were observed (Anastasopoulos et al. 2008). However, strictly speaking, segments with zero crash rates are "true zeroes" representing one of the real categories of a variable (crash rates) rather than "censored zeros" (Andersson et al. 2012). In this context, censoring refers to a situation where data on the dependent variable is lost (or limited) but data on explanatory factors are observed. For example, people of all income levels may be included in a survey sample, but for some reason, the income of high-income respondents may be "top-coded" as $100,000. As is evident, censoring is a defect in the survey sample, i.e., we know that a specific respondent's income is above $100,000 but we do not know the exact income.

On the other hand, corner-solution (as is the case in this study and almost in every safety outcome application) is not a data observability issue or defect in the sample. In the case of corner-solution, the dependent variable takes on the value of 1 (or zero or any value that characterizes the lower limit) with positive probability but is continuous random variable over strictly positive values. In effect, in our context, we have a rider who is solving a minimization problem, i.e., minimizing the injury severity. For some of the crash involved riders, the optimal outcome will be the corner solution, i.e., ISS = 1. As is evident, the data on ISS is perfectly observed and the lower limit (ISS = 1) is a true and intuitive outcome (rather than a censored lower limit), however, the fact that there is a spike at ISS = 1 warrants a methodological framework that treats the spike differently than the rest of distribution. Similar reasoning applies to crash rates on roadway segments or intersections. As Wooldridge (2010) makes it clear, applying a usual Ordinal Least Squares (OLS) regression in this setting is problematic (Wooldridge 2010). Fortunately, it follows that application of "censored" regression model, such as a Tobit model, mechanically fits well into corner-solution problems (Greene 2003), though it seems misleading to use the terminology of censoring, rather such models should be referred to as corner-solution models.[2] The generalized form of the structural equation in a tobit regression is given as (Yu et al. 2015):

$$Z_i^* = \beta X_i + \varepsilon_i; \quad (\mathrm{i} = 1, 2, \dots, \mathrm{N}) \tag{1}$$

Where Z_i is a latent variable that is observed for values greater than τ and censored otherwise. N indicates the number of total observations, X_i represents a vector of associated factors, β indicates values of parameters to be estimated, and ε_i indicates the associated error term following a normal distribution (Wali et al. 2018e)(i.e. $\mu = 0$ and $\sigma^2 = constant$). As in any latent variable model (Arvin et al. 2017, Hezaveh and Cherry 2019), the observed outcome (i.e., injury severity score of a motorcyclist i, Z_i) is mapped to the latent variable through the following measurement equation.

$$\begin{aligned} Z_i &= Z_i^* \ if \ Z_i^* > \tau \\ Z_i &= \tau_Z \ if \ Z_i^* \le \tau \end{aligned} \tag{2}$$

A likelihood function for a Tobit regression can be given as (Anastasopoulos et al. 2008, Yu et al. 2015):

$$L = \prod_i^N \left[\frac{1}{\sigma}\phi\left(\frac{Z-\mu}{\sigma}\right)\right]^{d_i} \left[1 - \Phi\left(\frac{\mu-\tau}{\sigma}\right)\right]^{1-d_i} \tag{3}$$

Where τ is the point in the distribution where the values are censored or simply left-spiked (corner-solution), Φ indicates a standard cumulative normal distribution function and ϕ indicates the standard normal density function. Typically, we set $\tau = 0$ and parametrize μ as a function of observed variables along with estimable parameters, βX_i. Thus, the likelihood function becomes:

[2] As such, we avoid using the terminology of "censoring" given the context under discussion and rather refer to the left-spike in the ISS distribution as "corner-solution." For convenience of readers, the use of term "corner-solution" can be visualized as the left-spike in distribution of ISS.

$$L = \prod_{i}^{N}\left[\frac{1}{\sigma}\phi\left(\frac{Z_i - \beta X_i}{\sigma}\right)\right]^{d_i}\left[1 - \Phi\left(\frac{\beta X_i}{\sigma}\right)\right]^{1-d_i} \tag{4}$$

And, after simple algebraic manipulations, the log-likelihood becomes:

$$lnL = \sum_{i=1}^{N}\left\{d_i\left(-ln\sigma + ln\phi\left(\frac{Z_i - \beta X_i}{\sigma}\right)\right) + (1-d_i)ln\left(1 - \Phi\left(\frac{\beta X_i}{\sigma}\right)\right)\right\} \tag{5}$$

The overall log-likelihood in Eq. 5 consists of two parts: the traditional regression for the uncensored observations, while the second part refers to the relevant estimable probabilities that specific observations are censored. It is important to mention that equation (1) assumes the effects of exogenous variables as fixed across all observations which may not be appropriate due to systematic variations in several unobserved factors. A random parameter model can be used to address this issue often referred to as unobserved heterogeneity (Huang and Abdel-Aty 2010, Mannering and Bhat 2014, Yu and Abdel-Aty 2014, Zhao and Khattak 2015, Mannering et al. 2016, Wali et al. 2017, Zhao and Khattak 2017, Wali et al. 2018b, Wali et al. 2018c, Khattak et al. 2019a). To address the unobserved heterogeneity associated with ISS in a corner-solution framework, random parameters can be included in a standard Tobit model as (Greene 2003):

$$\beta_i = \beta + \Gamma\sigma_i,\ \ (i = 1, 2, \ldots., N) \tag{6}$$

Where β indicates a randomly distributed term ($\mu = 0$ and $\sigma^2 = constant$); Γ indicates a symmetric matrix used to calculate the standard deviations of random parameters; and σ indicates a randomly distributed function ($\mu = 0$ and $\sigma^2 = 1$) (Kamrani et al. 2017, Kamrani et al. 2018, Wali et al. 2018e). Given this, the likelihood function becomes the log-likelihood function and can be written as (Anastasopoulos et al. 2012):

$$L = \sum_{\forall_i} ln \int_{\varphi_i} g(\varphi_i) P\left(\frac{Z_i^*}{\varphi_i}\right) d\varphi_i \tag{7}$$

In Eq. 7, $g(.)$ indicates the probability density function of the φ_i. Evaluation of the likelihood function in Eq. 7 requires integrating the probability model over the density function of φ_i. As opposed to Markov Chain Monte Carlo (MCMC) based methods to evaluating the multidimensional integral in Eq. 7 (Khattak et al. 2019b), a maximum simulated likelihood approach is applied in this study using 500 Halton draws (Bhat 2003, Wali et al. 2018e). As a result, the estimable parameter estimates are now allowed to vary across observations potentially due to systematic variations in unobserved factors (Khattak et al. 2019a). That is, for a specific variable found as a random parameter, we will have individual-specific β parameters. However, it is essential to mention that Eq. 6 assumes the random parameters to be uncorrelated, i.e., the source of heterogeneity is assumed to be independent. However, there is no reason to expect sources of heterogeneity being uncorrelated due to the very possibility of the presence of interactions among unobserved factors. While the traditional random parameter approach does allow capturing such unobserved factors, the potential interactive effects of distributional random parameters and subsequently of underlying unobserved factors are ignored. In the context under discussion (i.e., injury severity scores), such an extension is crucial given that several determinants of heterogeneity are likely to exhibit mixed and interactive effects on the rider's injury generating mechanisms. Thus, this study allows correlations between unobserved/random parameters. A variance-covariance matrix (V) is determined to investigate correlations among random parameters (Greene 2003):

$$V = \Gamma\Gamma' \tag{8}$$

Where Γ matrix is a non-restrictive function form used in determining non-zero off-diagonal elements of a variance-covariance matrix (Fountas et al. 2018b). The off-diagonal elements of a V-matrix can be calculated by taking squares of the standard deviation of the random correlated parameters, which are in fact zero if unobserved heterogeneity is assumed to be uncorrelated (Greene 2003). The following equation can be employed while calculating the standard deviations of the correlated random parameters (Fountas et al. 2018b):

$$\delta_j = \sqrt{(\delta_{k,k^2} + \delta_{k,k-1^2} + \delta_{k,k-2^2} + \cdots + \delta_{k,1^2})} \tag{9}$$

In the above equation δ_j are the standard deviations of the random parameters; $\delta_{k,k-1,}\delta_{k,k-2,\ldots,}\delta_{k,1}$ are the off-diagonal elements associated with any specific random parameter j; and $\delta_{k,k}$ represents the diagonal elements of the matrix Γ. Note that usually the literature does not calculate the statistical significance of standard deviation in the correlated random parameters. It is important to calculate this significance as it allows us to examine if the heterogeneity in the magnitudes of the effects of correlated random parameters is indeed statistically significant. Given the observation-specific estimates of the standard deviations (i.e. random parameters) from the software, t-stats and standard errors for each of the random parameters can be calculated as (Fountas et al. 2018b):

$$SE_{\sigma j} = \frac{S_{\sigma_{jn}}}{\sqrt{N}} \tag{10}$$

Whereas, $SE_{\sigma j}$ represents the standard deviation; $S_{\sigma_{jn}}$ indicates the standard deviation for observation-specific σ_{jn}; and N indicates the total number of observations in the dataset analyzed. The t-stats can be calculated while using the post-estimation analytical procedure as follow:

$$t_{\delta_j} = \frac{\sigma_j}{SE_{\sigma j}} \tag{11}$$

And, following Fountas et. al (2018), the correlation coefficients between any two random parameters can be given as (Fountas et al. 2018b):

$$Cor_{(X_{j,n,}X_{j',n,})} = \frac{COV(X_{j,n,}X_{j',n})}{\sigma_{j,n}\sigma_{j',n}} \tag{12}$$

In the above equation, $COV(X_{j,n,}X_{j',n})$ indicates the covariance matrix of the two independent variables (i.e. $j\ and\ j'$ with random parameters) whereas $\sigma_{j,n}\sigma_{j',n}$ indicate their respective standard deviations. To investigate the effect of a unit change in an explanatory variable on a response outcome in a Tobit setup, three possible marginal effects can be calculated related to different expected values (Sigelman and Zeng 1999). That is, depending on the context, we can evaluate the expected value of the latent variable (Z_i^* in Eq. 1), expected value of actual response variable (Z_i in Eq. 2) or expected value of actual response variable for cases that are not censored (i.e., $Z_i|Z_i > 0$). The marginal effect on the expected value of actual response variable Z_i for uncensored observations can be calculated as:

$$\frac{\partial E[Z_i|Z_i>0]}{\partial X_i} = \beta_i\left\{1 - \lambda(\alpha)\left[\frac{X_i\beta}{\sigma} + \lambda(\alpha)\right]\right\} \tag{13}$$

Where:

$$\lambda(\alpha) = \phi\left(\frac{X_i\beta}{\sigma}\right) \Big/ \Phi\left(\frac{X_i\beta}{\sigma}\right) \tag{14}$$

The formulation in Eq. 13 and Eq. 14 indicates how a one-unit change in a specific explanatory factor affects the uncensored observations. As such, this set of marginal effects will provide insights into the effects of explanatory factors on cases where the response outcome (ISS) is not at corner solution, i.e., ISS > 1. We note that the marginal effects calculated using Equations 13 and 14 are very useful in the case where Tobit model is applied in the presence of "true censoring". However, in the current application, the effects of explanatory factors on cases where the response outcome is at the corner (i.e., ISS = 1) are also of interest, given that an injury severity score of 1 represents a true and intuitive outcome (see discussion above). Thus, we calculate the effect of a unit change in X on the expected value of Z_i (both censored and uncensored) as follows:

$$\frac{\partial E[Z_i]}{\partial X_i} = \Phi\left(\frac{X_i\beta}{\sigma}\right)\beta_i \tag{15}$$

In Equation 15, note that $\Phi\left(\frac{X_i\beta}{\sigma}\right)$ is a scale factor representing the probability of observing an uncensored observation at specific values of X. As the scale factor approaches one, fewer censored observations are expected, and thus the scale factor becomes unimportant with the actual coefficient (β_i) then providing the marginal effect at specific values of X. Finally, the effect of a unit change in X on the probability of an observation being uncensored is:

$$\frac{\partial \Pr(Z_i > 1 | X_i)}{\partial X_i} = \phi\left(\frac{X_i\beta}{\sigma}\right)\frac{\beta_i}{\sigma} \tag{16}$$

As noted earlier, the choice of a marginal effect depends on the application. In our case, $E[Z_i]$ seems to be the most useful interpretation of the effects of key covariates. Also, Wooldridge (2010) and Greene (2003) seem to side with $E[Z_i]$ as the most useful which applies to our context as well given that this a corner-solution setup[3] (Greene 2003, Wooldridge 2010). For estimation of uncorrelated and correlated random parameter Tobit models, 500 Halton draws are used for parameter estimation, whereas the distributions tested for random parameters are normal, lognormal, triangular, uniform, and Weibull distributions. For comparing the different models, goodness-of-fit measures such as likelihood ratio test, Akaike Information Criteria (AIC) are used (Washington et al. 2010, Wooldridge 2010, Wali et al. 2018d).

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[3] We note that the different types of marginal effects can be substantially different in the context of fixed parameter Tobit model. However, in the context of random parameter models, the difference between different marginal effects based on expected values can be smaller. For instance, the scale factor $\Phi\left(\frac{X_i\beta}{\sigma}\right)$ in the the formulation of marginal effects for censored and uncensored observations (Equation 15) depend on the unobserved components (σ) in the Tobit likelihood function. In the fixed parameter model, the σ parameter is likely larger as all unobserved factors (beyond the ones captured by observed variables) get into σ. With a larger σ parameter in the denominator, the $\left(\frac{X_i\beta}{\sigma}\right)$ term gets smaller and thus the cumulative probability or scale factor, $\Phi\left(\frac{X_i\beta}{\sigma}\right)$, becomes significantly smaller than 1. The smaller the scale factor is, the more the difference between different marginal effects will be (Equations 13 through 16). However, for uncorrelated and correlated random parameters, as much of the variation in unobserved factors is tracked through the random β coefficients themselves, the σ parameter is (and should be) significantly smaller than the one in fixed-parameter counterpart. Thus, $\left(\frac{X_i\beta}{\sigma}\right)$ gets relatively larger (assuming the linear prediction ($X_i\beta$) is on-average similar for the fixed and random parameter counterparts), and the scale factor $\Phi\left(\frac{X_i\beta}{\sigma}\right)$ eventually approaches 1. As such, the difference between the three marginal effects should theoretically decrease for random parameter models, and in cases where the scale factor approaches 1, though not a formal result, the three marginal effects should be similar. We discuss the different marginal effects for fixed and random parameter models in Section 3.2., however, we mainly focus on interpreting $\frac{\partial E[Z_i]}{\partial X_i}$ in discussing the key findings.

In terms of model building, we derived all of the models from a systematic process in order to include the most important variables on the basis of statistical significance, specification parsimony, and intuition (see section 3.2). In arriving at a final plausible specification, key variables based on the scope of the current study were first included in the model specification. For instance, rider conspicuity related factors were first included, and those factors that emerged as statistically significant were retained. Next, rider experience, helmet-related, and rider apparel related factors were included. Finally, other important variables such as rider and crash-specific factors, and alcohol/drug intake related variables were included as controls. In doing so, careful attention was given to the issue of multicollinearity (as detailed later in section 3.1). That is, all key variables included in the final model specification exhibit a VIF value of less than 10, indicating the absence of problematic multicollinearity.

3. RESULTS

3.1. Descriptive Statistics

Given the key focus of this study, the descriptive statistics of key variables are presented in Table 1. Table 1 presents the summary and distributional statistics for the injury severity score (response variable) and factors related to rider experience, rider apparel and conspicuity, helmet related factors, alcohol or drug intake, rider-, and crash-specific conditions (Table 1). Out of 351 riders involved in crashes, exact injury information is available for 321 riders, whereas, the rest of riders were injured with "unknown" severity. Thus, the descriptive statistics shown in Table 1 are for riders with known injury severity (N = 321). Referring to Table 1, the mean rider injury severity score (ISS) is 10.320 with a standard deviation of 15.976. Note that an ISS score of greater than 9 can be considered as equivalent to a serious injury (Stevenson et al. 2001). The distribution of the injury severity score (ISS) is sparse in that the interquartile range (third quartile minus first quartile) is 37 (see Table 1). Importantly, the injury severity scores for as much as 78 crashes are spiked at 1 (see Table 1). As discussed in methodology, this is a classic example of corner solution (and not censoring per se) and as such a Tobit modeling framework can be employed to treat the spike at 1 differently than the rest of the distribution for obtaining unbiased and consistent estimates (see discussion in methodology section).

Coming to rider experience related factors in Table 1, around 20% of the riders reported gaps in their riding experience whereas only 5% of the crash involved riders had an experienced rider course in past. The MCCS provides unique information about the appropriateness of rider apparel. For instance, 14% of riders had retroreflective upper body clothing, 34% of riders had their upper clothing being motorcycle-specific, whereas 17% of the riders had their shoes being motorcycle-specific. Note that inappropriateness of rider clothing is one of the "high-priority" key risk factors as per the U.S. DOT's National Agenda for Motorcycle Safety (NHTSA 2013).

Related to helmet-related factors, around 43% of the riders wore a black helmet, whereas around 19% of the riders wore multicolor, white, or silver/grey colored helmets (Table 1). Importantly, only 55% of the riders had an acceptable helmet fit.[4] This is important as a poor helmet fit can be one of the key reasons for head injuries among riders (Rivara et al. 1999). The dataset also provides information about the coverage of the helmet (see Table 1).

Among the injury crashes analyzed in this study, around 7% of the riders were found to have a positive Blood Alcohol Concentration[5] (BAC). Whereas, another 6% of the riders took depressants or

[4] Of the 321 riders analyzed in this study, information on helmet use is available (coded) for 317 riders. Of these 317 riders, 313 (98.7%) of the riders wore a helmet whereas only 4 of them either did not wear a helmet or helmet use was unknown. Note that California is one of the universal helmet law states that require the wearing of helmets meeting federal safety standards by all riders and passengers (https://www.iihs.org/iihs/topics/laws/helmetuse/mapmotorcyclehelmets).

[5] Out of the 321 riders analyzed in this study, note that data on BAC are available for 80 riders (33.1% of the sample) and are recorded in 16 finely tuned categories ranging from 0 milligram per deciliter (mg/dl) BAC to 0.28 or greater mg/dl BAC. The remaining 241 riders (75% of the data) were not tested for BAC (NHTSA 2017). Of those who were tested for BAC (N = 80), 55 crash-involved riders (68.7% of the tested riders) were found to have BAC equaling 0 mg/dl. Whereas, the rest of 25 riders had a positive BAC with almost all of them legally impaired (i.e., BAC of 0.08

multiple drugs. Related to rider-specific factors, the average height and age of the crash-involved riders was 5.8 feet and 36 years respectively. Referring to Table 1, around 63% of the riders had some type of physical impairment. Among the crash-specific factors, the average speed before impact was 36.2 mph. Importantly, the dataset provides information about the time the riders had from the key contributing event (precipitating event) to impact. For example, almost 50% of the riders had more than 2.3 seconds between the precipitating event and impact (see Table 1). Whereas, around 49% of the riders had at least 9 feet distance covered from their point of impact to their point of rest (Table 1). Overall, based on the distributions of key variables, the data seem to be of reasonable quality.

Finally, we examined for the presence of potential confounding variables in the data used. Specifically, the goal is to analyze multicollinearity in terms of the intercorrelation of the regressors on the model variances. Ignoring or not accounting for confounding variables in the analysis can influence model parameters and lead to biased results in terms of revealing a statistically significant relationship between an observed variable and outcome at times when the observed relationship may be an outgrowth of another confounding variable correlated with the outcome of interest (in our case the injury severity score.) A confounding variable can be either observed or unobserved in the data. For instance, the observed variable "gap exists between riding" (see Table 1) may be confounded with age or experience of the rider. That is, a young or new rider is not likely to have a gap in riding, or at least not having a long gap.[6] To identify potential confounding variables among the "observed" regressors, potential intercorrelations of the regressors can be examined. Variance Inflation Factors (VIF) are shown in Table 1 for all the regressors. A VIF statistic shows the severity of multicollinearity among variables, with a value of greater than 10 suggesting problematic multicollinearity (Chatterjee and Price 1991). As can be seen in Table 1, the VIF statistics for all the key regressors are no greater than 2.92, indicating the absence of problematic collinearity. As discussed earlier, note that the methodological framework presented in Section 2.3 fully accounts for the presence of potential "unobserved" confounders or confounding effects due to omitted variables.

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mg/dl or greater.) For further details, see (NHTSA 2017). As such, in interpreting the coefficient associated with this dummy variable (later in results and discussion section), the interpretation would be an increase in ISS for those with positive BAC compared to both riders who were tested (and had 0 BAC) and those who were not tested (BAC missing). As we have categorized missing data as no alcohol, the findings presented related to BAC are actually conservative as there is a chance that riders with no data on BAC may had positive BAC. However, as riders who were not tested by the investigators are likely to be sober (i.e., no positive BAC content), the base value of the dummy variable is reasonable and relatively cleaner.

[6] This intuitive hypothesis, i.e., a young or new rider not being likely to have a gap in riding, is also supported by the data. For instance, of the 87 riders aged 25 years or less, 79 (90.8% of the riders) did not have a gap in their riding. For the eight young riders (9.2%) who reported a gap, the gaps are likely shorter.

TABLE 1: Descriptive Statistics of Key Variables

Variables	Mean	SD	Min	Max	VIF
Dependent Variable: Rider Injury Severity Score	10.320	15.976	1	75	
	1st Quartile = 19.50; Midpoint = 38; 3rd Quartile = 56.500; Spike at 1 = 78 observations				
Rider Experience Related Factors					
Gap exists between riding (1/0)	0.20	0.40	0	1	1.45
Experienced rider course (1/0)	0.05	0.21	0	1	1.14
Rider Apparel & Conspicuity Related Factors					
Upper body clothing retroreflective (1/0)	0.14	0.35	0	1	1.57
Upper clothing MC specific (1/0)	0.34	0.47	0	1	1.81
Shoes MC specific (1/0)	0.17	0.37	0	1	1.35
Blue color waist down clothing (1/0)	0.37	0.48	0	1	1.43
Helmet color (multicolor)	0.07	0.26	0	1	1.47
Helmet color (White)	0.06	0.24	0	1	1.33
Helmet color (silver, grey)	0.06	0.23	0	1	1.25
Helmet color (Black)	0.43	0.50	0	1	2.01
Helmet Related Factors					
Half face motor vehicle, motorcycle helmet (1/0)	0.11	0.31	0	1	1.25
Acceptable helmet fit (1/0)	0.55	0.50	0	1	2.92
Alcohol/Drugs Intake					
Positive BAC (1/0)	0.07	0.26	0	1	1.23
Rider took depressant or multiple drugs (1/0)	0.06	0.23	0	1	1.13
Rider Specific Factors					
Height of rider	5.86	0.28	4.92	6.75	1.14
Age of rider at time of crash (years)	36.06	14.21	16	73	1.38
Rider has no physical impairment (1/0)	0.37	0.48	0	1	1.88
Ethnicity: Black rider (1/0)	0.05	0.21	0	1	1.16
Crash Specific Factors					
Travel speed before crash (mph)	36.23	16.24	0	96	1.2
Time in seconds from precipitating event to impact (1 if > 2.3, 0 otherwise)	0.50	0.50	0	1	1.13
Distance in feet between POI to POR (1 if > 9, 0 otherwise)	0.49	0.50	0	1	1.08
Two-way undivided highway (1/0)	0.31	0.46	0	1	1.13
Level grade (1/0)	0.55	0.50	0	1	1.09
MC running off roadway, no OV involvement (1/0)	0.08	0.27	0	1	1.25
Negotiating a curve, constant speed (1/0)	0.12	0.33	0	1	1.11

Notes: SD is standard deviation; N = 321 crashes except height of rider in feet (available for N = 319), age of rider in years (available for N = 318), and travel speed before crash in mph (available for N = 300 crashes.); MC is motorcycle; OV is other vehicle; POI is point of impact; POR is point of rest.

3.1.2 Comparison of ISS and AIS:

To further illustrate the distribution of ISS and understand the similarities/differences between ISS and AIS, Table 2 provides the cross-tabulation of ISS and AIS categories. To do so, ISS is first mapped to AIS using the ranges provided in (Stevenson et al. 2001). The ranges are: 1) an ISS of 1 to 3 as minor injury, 2) ISS of 4 to 8 as moderate injury, 3) ISS of 9 to 15 as serious injury, 4) ISS of 16 to 24 as severe injury, 5) ISS of 25 to 35 as critical injury, and 6) ISS of 36 to 75 as maximum (untreatable) injury. Once ISS is mapped to AIS, we performed cross-tabulation analysis in order to understand the strength of association between the two injury severity measures (Table 2).

In Table 2, the number at the top of each cell is the frequency (shown in white cells), the second number is the row percentage, i.e., it sums to 100 percent going across the table as indicated by light grey cells. Specifically, the row percentages show that for a given category of Abbreviated Injury Scale (AIS), what is the distribution of different categories of ISS? Finally, the third number in each cell is the column percentage and sums up to 100% going down the table (indicated by dark grey cells). These numbers show that for a given category of ISS, what is the distribution of different categories of AIS? Going along a specific row (indicated in light grey cells) or a specific column (indicated in dark grey cells), the row and column percentages can be interpreted as chance, or probabilities if divided by 100.

Overall, it is observed that AIS and ISS have a strong strength of association with a Kendall's tau rank coefficient of 0.911 (Table 2). However, there are some contrasts between the two as well, and these contrasts can be interpreted as differences in how AIS and ISS classify injuries of a person particularly when the latter considers the possibility of multiple injuries sustained by a rider.

For instance, of all the 128 riders who sustained minor injuries according to ISS (i.e., ISS ranging between 1 and 3), 94.53% of those were also classified as minor injuries by AIS, whereas, the rest (i.e., 5.47%) were classified as moderate, serious, or severe injuries by the AIS (see Table 2). Importantly, AIS classifies the injuries to 103 riders as moderate injuries, of which only 82.52% are also classified as moderate injuries by ISS (i.e., ISS ranging between 4 to 8), whereas 13.59% and 3.88% are classified as serious injuries (ISS of 9-15) and minor injuries (ISS of 1-3) by ISS (see Table 2).

Contrasts in how ISS and AIS classify serious and severe injuries are significant. For instance, of all the riders' injuries classified as severe injuries (ISS of 16-24) by ISS, only 29.41% of those are classified as severe injuries by AIS, whereas, a significant 70.59% of those are classified as serious injuries by AIS (Table 2).

Perhaps the most important insight from the cross-tabulation relates to how AIS and ISS classify "maximum (untreatable)" injuries. According to AIS, injuries to 13 riders are "maximum (untreatable)", 100 percent of which are classified as "maximum (untreatable)" by ISS as well (see Table 2). That is, the injury severity score does not misclassify an injury as "maximum (untreatable)". Contrarily, of all the riders with maximum (untreatable) injuries as per ISS (i.e., 24 riders), only 54.17% of them are classified as maximum (untreatable) injuries by AIS as well, whereas, the rest are classified as severe or critical injuries (see Table 2). Similar patterns can be observed when the classification of injuries into "critical injuries" by AIS and ISS is compared. This finding is important as it suggests that AIS can underestimate the 'true' injury severity sustained by a rider. For this dataset, it seems that the rate of misclassification by AIS is higher for more severe injuries. Finally, the distributions of AIS and ISS for the sampled crashes are provided in Figure 1.

TABLE 2: Cross-Tabulation of Abbreviated Injury Scale (AIS) and Injury Severity Score

ISS Categories / AIS Categories	ISS (1-3): Minor	ISS (4-8): Moderate	ISS (9-15): Serious	ISS (16-24): Severe	ISS (25-35): Critical	ISS (36-75): Maximum (Untreatable)	Total
Minor Injury	121	1	0	0	0	0	122
	99.18	0.82	0	0	0	0	100
	94.53	1.12	0	0	0	0	38.01
Moderate Injury	4	85	14	0	0	0	103
	3.88	82.52	13.59	0	0	0	100
	3.13	95.51	26.42	0	0	0	32.09
Serious Injury	1	2	39	12	1	0	55
	1.82	3.64	70.91	21.82	1.82	0	100
	0.78	2.25	73.58	70.59	10	0	17.13
Severe Injury	2	0	0	5	6	2	15
	13.33	0	0	33.33	40	13.33	100
	1.56	0	0	29.41	60	8.33	4.67
Critical	0	1	0	0	3	9	13
	0	7.69	0	0	23.08	69.23	100
	0	1.12	0	0	30	37.5	4.05
Maximum (Untreatable)	0	0	0	0	0	13	13
	0	0	0	0	0	100	100
	0	0	0	0	0	54.17	4.05
Total	128	89	53	17	10	24	321
	39.88	27.73	16.51	5.3	3.12	7.48	100
	100	100	100	100	100	100	100
Measures of Association	Pearson χ^2 (25) = 855.1792; p-value = 0.000						
	Kendall's τ_b rank coefficient = 0.9111; Asymptotic Standard Error = 0.019						

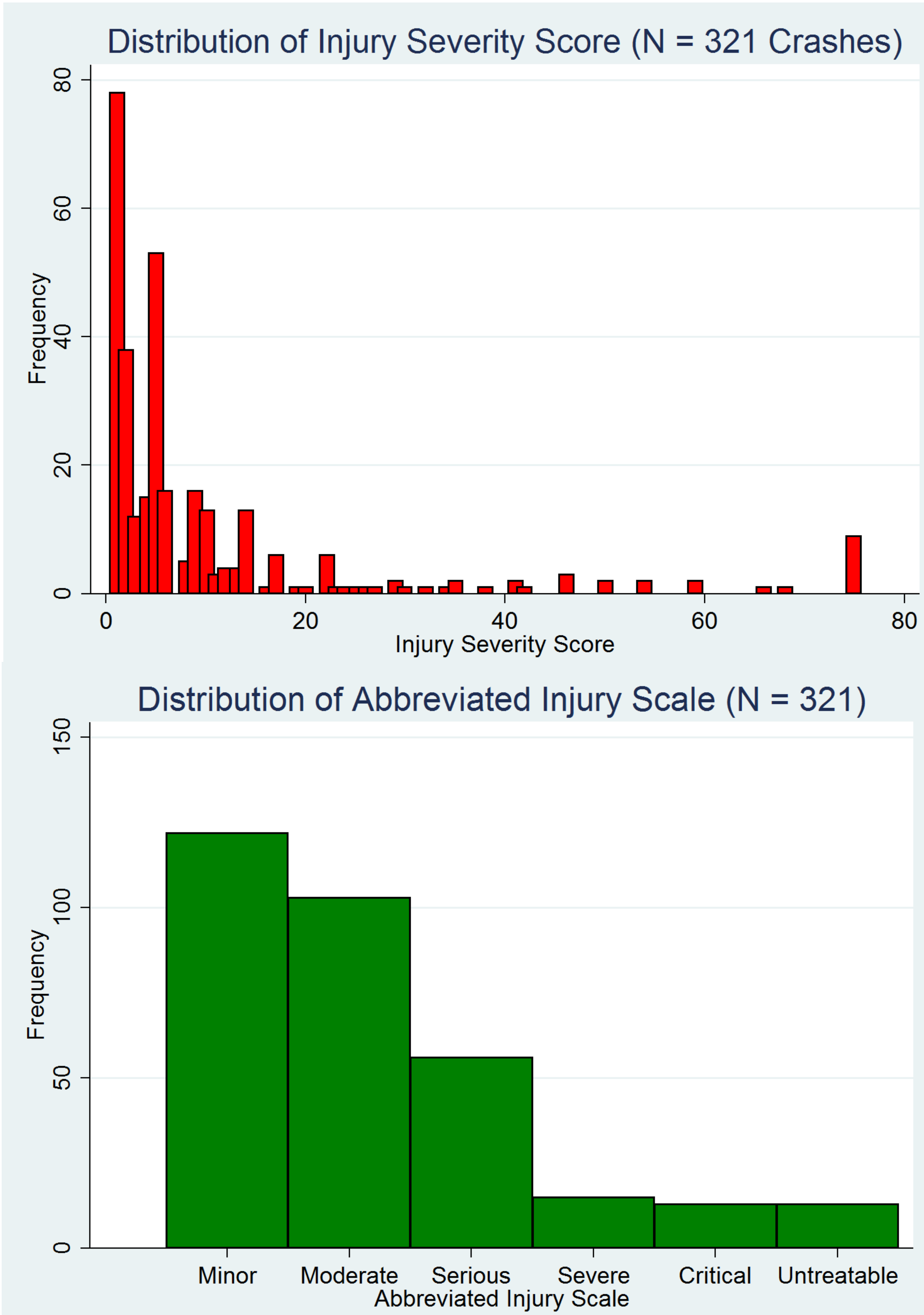

FIGURE 1 Distribution of Injury Severity Scores and Abbreviated Injury Scale for the Sampled Crashes

3.2. Modeling Results

The detailed empirical analysis presented next focuses on analyzing the correlations between a rider's Injury Severity Score (ISS) and different key explanatory factors shown in Table 1. Owing to the distributional nature of the response outcome, a Tobit modeling framework is employed in a "corner-solution" setup to relate ISS with key risk factors given a motorcycle crash.[7] Advanced modeling schemes are explored to fully account for both correlated and uncorrelated unobserved heterogeneity in motorcycle injury severity analysis.

First, fixed parameter Tobit models (Equation 1) are developed in which the parameter estimates are constrained to be fixed across all observations. Several specifications were tried, and Table 3 presents the results of the final fixed parameter Tobit model, where 15 explanatory factors were statistically significant at a 95% confidence level. As discussed earlier, unobserved heterogeneity and omitted variable bias can be suspected and its presence prevents the establishment of precise and unbiased correlations between the injury severity score and key risk factors. Thus, uncorrelated random parameter Tobit models (URPT) (Equation 6) are estimated by allowing the parameter estimates to vary across observations owing to the possibility of systematic variations in unobserved factors that can influence the injury severity score. Parameter estimates that exhibited both statistically significant means and standard deviations are treated as random parameters. A total of six explanatory factors were found to be normally distributed random parameters suggesting that the effects of these factors vary significantly across the observations (discussed later). The goodness-of-fit results of best-fit fixed and uncorrelated random parameter Tobit models (URPT) are presented in Table 3. Whereas, the variance covariance matrix for the random parameter Tobit model is shown in the upper panel of Table 4 with t-statistics of the variance estimates in brackets. The fact that the off-diagonal entries in the variance-covariance matrix of the random parameter Tobit are zero indicates the assumption of uncorrelated random parameters (see top panel of Table 4). Compared to the fixed parameter model, the AIC of uncorrelated random parameter model is lower, and which indicates the statistical supremacy of uncorrelated random parameter Tobit model in tracking unobserved heterogeneity against its fixed parameter counterpart (Table 3).

A typical approach used in the literature to account for unobserved heterogeneity is to employ the conventional random parameter modeling framework (as is done above). In doing so, a restrictive formulation for the covariance matrix of random parameters is applied (see methodology section), and which does not allow for potential correlations among the explanatory factors treated as random parameters. That is, the random parameters tracking the possible unobserved heterogeneity are assumed to be uncorrelated and which is rather a very restrictive assumption. For instance, it is possible that potential unobserved factors are commonly shared among the pairs of the random parameters, in which case several determinants of heterogeneity are likely to exhibit mixed and interactive effects on the rider's injury generating mechanisms. Failure to account for correlation effects among randomly distributed effects of explanatory factors can result in several misspecification issues, such as biased, inconsistent parameter estimates, and/or erroneous inferences.

[7] Note that just for ease of presentation, we use the terms "censoring, censored/uncensored outcomes" in laying out the key results when we indeed mean to refer to "corner-solution" (see discussion in section 2.3).

TABLE 3: Estimation Results for Fixed Parameter Tobit, Uncorrelated Random Parameter Tobit (URPT), and Correlated Random Parameter Tobit (CRPT) Models

	Fixed Parameter Tobit			**Uncorrelated Random Parameter Tobit (URPT)**			**Correlated Random Parameter Tobit (CRPT)**		
Variables	***β***	***SE***	***z-score***	***β***	***SE***	***z-score***	***β***	***SE***	***z-score***
Negotiating a curve, constant speed (1/0)	-6.39	2.82	-2.27	-4.69	0.69	-6.83	-2.89	0.48	-6.01
Travel speed before crash (mph)	0.30	0.06	5.14	0.29	0.01	22.22	0.28	0.01	29.28
Time indicator: Time in seconds from precipitating event to impact (1 if > 2.3, 0 otherwise)	6.27	1.83	3.42	2.36	0.41	5.81	3.07	0.28	10.88
standard deviation*	---	---	---	*11.43*	*0.28*	*40.53*	*11.85*	*0.22*	*53.86*
Distance indicator: Distance in feet between POI to POR (1 if > 9, 0 otherwise)	3.58	1.80	1.98	4.10	0.40	10.14	1.30	0.28	4.55
standard deviation*	---	---	---	*13.38*	*0.30*	*44.36*	*15.04*	*0.28*	*53.75*
Half face motor vehicle, motorcycle helmet (1/0)	5.95	3.12	1.92	4.89	0.71	6.90	5.31	0.51	10.51
standard deviation*	---	---	---	*9.63*	*0.67*	*14.32*	*7.45*	*0.13*	*56.80*
Acceptable helmet fit (1/0)	-8.67	2.99	-2.9	-9.60	0.65	-14.84	-8.82	0.46	-19.28
standard deviation*	---	---	---	*4.48*	*0.27*	*16.88*	*5.57*	*0.10*	*55.57*
Positive BAC (1/0)	10.43	3.94	2.65	2.77	0.93	2.99	15.62	0.70	22.41
standard deviation*	---	---	---	*18.28*	*0.87*	*21.00*	*31.80*	*0.52*	*61.08*
Two-way undivided highway (1/0)	2.25	2.00	1.12	4.20	0.46	9.18	4.65	0.32	14.52
Level grade (1/0)	4.77	1.82	2.62	4.10	0.41	9.92	3.92	0.29	13.57
MC running off roadway, no OV involvement (1/0)	8.01	3.40	2.36	7.35	0.78	9.38	5.58	0.60	9.31
standard deviation*	---	---	---	*23.43*	*0.83*	*28.17*	*28.03*	*0.49*	*57.58*
Helmet color (multicolor)	19.26	3.84	5.02	15.47	0.82	18.95	17.03	0.57	30.10
Helmet color (White)	16.87	4.05	4.16	9.70	0.95	10.20	9.85	0.68	14.42
Helmet color (silver, grey)	-5.46	4.58	-1.19	-7.78	1.16	-6.70	-7.56	0.84	-8.95
Helmet color (Black)	7.12	2.48	2.87	5.47	0.55	10.00	4.25	0.40	10.75
Experienced rider course (1/0)	-10.23	4.41	-2.32	-7.73	1.07	-7.21	-8.21	0.77	-10.68
Gap exists between riding (1/0)	2.22	2.56	0.86	4.14	0.59	7.07	3.39	0.42	8.14
Upper clothing MC specific (1/0)	5.89	2.45	2.4	4.42	0.54	8.18	3.21	0.39	8.33
Shoes MC specific (1/0)	-5.00	2.68	-1.87	-5.61	0.60	-9.30	-5.95	0.44	-13.56
Upper body clothing retroreflective (1/0)	-3.77	3.05	-1.24	-2.05	0.67	-3.05	-1.89	0.48	-3.91
Height of rider	-6.65	3.31	-2.01	-3.70	0.74	-5.00	-1.68	0.54	-3.09
Blue color waist down clothing (1/0)	1.94	2.12	0.91	5.32	0.48	11.18	5.45	0.34	16.08
Rider took depressant or multiple drugs (1/0)	8.07	3.91	2.06	3.00	0.96	3.14	2.30	0.67	3.41
Age of rider at time of crash (years)	0.07	0.07	0.92	0.04	0.02	2.39	0.03	0.01	2.96
Rider has no physical impairment (1/0)	-5.15	2.46	-2.09	-3.72	0.55	-6.76	-2.96	0.39	-7.51
Ethnicity: Black rider (1/0)	-3.84	5.02	-0.76	-5.88	1.23	-4.79	-5.93	0.91	-6.53
Constant	22.81	19.41	1.17	10.38	4.34	2.39	-0.71	3.16	-0.23
Disturbance (standard deviation)	14.25	0.68	20.82	2.93	0.14	21.59	2.02	0.09	22.70
LL(B)	-975.154			-935.1758			-914.9497		
AIC	2004.3			1936.4			1925.9		

Notes: **β** is parameter estimate; (---) indicates not applicable; (*) The standard deviations, standard errors, and t-statistics of correlated random parameters are derived from estimation results using the procedure outlined in methodology section.

To account for this important methodological concern and to capture the complexity of injury generating mechanisms, correlated random parameter Tobit models (CRPT) are estimated. In doing so, the random parameters can be correlated with each other, i.e., the off-diagonal elements of the variance-covariance matrix of URPT are now estimated from the data at hand, thus termed as CRPT. The variance–covariance matrix for the random parameter distribution is set to follow a multivariate normal distribution. The results of correlated random parameter Tobit model (CRPT) are shown in Table 3, whereas lower panel of Table 4 presents the diagonal and off-diagonal elements of the covariance matrix for random parameters, the associated t-statistics in brackets and the estimated correlation matrix of all random parameters in parenthesis (see lower panel of Table 4). As can be seen in Table 3, the AIC of CRPT is significantly lower than the AIC of URPT model, suggesting that the unobserved heterogeneity discovered through URPT model was indeed correlated and that factors determining heterogeneity exhibit interactive effects on the injury severity score. Overall, as shown in Table 3, a total of six correlated random parameters are found in this study, and which are 1) Time in seconds from precipitating event to impact (1 if > 2.3, 0 otherwise), 2) Distance in feet between point of impact to point of rest (1 if > 9, 0 otherwise), 3) Half face motor vehicle, motorcycle helmet (1/0), 4) Acceptable helmet fit (1/0), 5) Positive Blood Alcohol Concentration (1/0), and 6) Motorcycle running off roadway, no other vehicle involvement (1/0). This means that the associations of these factors with the injury severity score vary statistically significantly across the sampled observations due to systematic variations in unobserved factors. We present the interpretation of (correlated) random parameters in the subsequent discussion.

Finally, to better interpret the results of the Tobit models, Table 5 presents the marginal effects of the explanatory factors on different types of expected values for the best-fit correlated random parameter Tobit model. See the methodology section for different marginal effects and expected values from Tobit models. In particular, estimates of $\frac{\partial E[Z_i|Z_i>0]}{\partial X_i}$ (marginal effect on expected value of the injury severity score (ISS) given ISS is uncensored), $\frac{\partial E[Z_i]}{\partial X_i}$ (marginal effect on expected value of ISS – both censored and uncensored), and $\frac{\partial \Pr(Z_i>1|X_i)}{\partial X_i}$ (effect of unit change on probability of being uncensored) are provided in Table 5. To highlight differences in magnitudes of effects, the different types of marginal effects for fixed parameter Tobit and uncorrelated random parameter Tobit are also shown in Table 5. Before discussing the key results, we present key observations related to the different types of marginal effects. Overall, for the fixed parameter model, significant differences can be observed in terms of the effect(s) of unit change in explanatory factor(s) on expected (uncensored and censored) value of ISS (denoted by ME-1 in Table 5) and on uncensored expected values of ISS (denoted by ME-3 in Table 5). For instance, compared to non-retroreflective clothing, retroreflective upper body clothing reduces the injury severity score by 2.58 units (ME-1 in Table 5) and by 1.81 units for uncensored injury severity scores (ME-3 in Table 5). Likewise, the effects of a unit change in explanatory factors on the probability of being uncensored are substantial (see Table 5). For example, retroreflective upper body clothing reduces the probability of having an uncensored observation (where uncensored observations reflect higher severity compared to censored ISS of 1) by 9.40 percentage points. That is, retroreflective upper body clothing on-average reduces the probability of observing higher injury severity scores. However, for the uncorrelated random parameter model (panel 2 in Table 5), the differences between the marginal effects decrease substantially (as one would expect). As an example, according to uncorrelated random parameter Tobit model, retroreflective upper body clothing reduces the injury severity score (for both censored and uncensored observations) by 2.04 units, whereas a reduction of 1.98 points for the uncensored injury severity score (see panel 2 in Table 5). This smaller difference between the two marginal effects is intuitive (as explained in footnote 3). For the fixed parameter Tobit model, the standard deviation of disturbance term (capturing unobserved factors) is 14.25, whereas, it is 2.93 for the uncorrelated random parameter Tobit model (see Table 3). With such a small standard deviation of disturbance term for uncorrelated random parameter model (compared to disturbance term in fixed parameter counterpart), the scale factor approaches 1 and thus the difference between the three marginal effects gets smaller (as marginal effects are a function of σ, see Equations 13 through 16). Similarly, for correlated random parameter model (panel 3 in Table 5), as the disturbance term is the smallest among the three methodological alternatives, the two marginal effects for uncensored/censored expected values of ISS and uncensored expected values of ISS are approximately similar. Overall, in the context under discussion, these findings importantly suggest that evaluating effects of unit change in predictor on censored/uncensored and on uncensored outcomes (which is typically critical in the context of fixed parameter models) may not be that relevant for correlated or uncorrelated random parameters. However, these observations while important should be interpreted with caution as they are specific to this empirical application and should be tested in other safety applications.

Interesting findings regarding the correlations between a rider's injury severity score and key explanatory variables pertaining to the study objectives are discussed next.[8] In discussing the effects of key policy-sensitive factors, we interpret the effects of a unit change in the predictor on the expected value of the injury severity score (both censored and uncensored).

[8] Even though the association between ISS and AIS has been descriptively explored in section 3.1.2, a reasonable concern can be whether similar conclusions (as shown by ISS-based models) could be drawn from models based on AIS, as AIS is also a popular injury severity scale. We thank the anonymous reviewer for highlighting this possibility. Since ISS (censored continuous outcome) and AIS (ordered outcome) are empirically different in nature, two sets of models with AIS and ISS as dependent variables cannot be explicitly compared as the β parameter estimates from the two models exhibit different interpretations. Alternatively, this also implies that the correlated and uncorrelated Tobit modeling framework (as in case of ISS) cannot be employed for AIS given its ordinal nature. However, to gain a high-level insight into the comparability of results from AIS and ISS-based models, we estimated a fixed-parameter ordered probit model with AIS as response outcome (Greene 2003, Ahmad et al. 2018, Ahmad et al. 2019). All variables included in ISS-based models (Table 3) were retained as explanatory variables in AIS-based ordinal model. The ordered probit model with AIS as response outcome was then compared with ISS-based fixed-parameter Tobit model (Table 3) in terms of, (1) direction of association for key variables, (2) and its statistical significance. We found out that the direction of associations revealed by ISS-based models (shown in Table 3) and AIS-based model (not shown here) were exactly similar for all the explanatory variables. That is, for a specific explanatory factor (such as rider speed and age), both models revealed similar direction of association (i.e., a negative relationship of rider speed and age with injury severity.) However, some contrasts were found in terms of statistical significance. For instance, three variables (two-way undivided highway, gap exists between riding, and blue color waist down clothing) were statistically significant at 90% level in AIS-based model whereas statistically insignificant in ISS-based fixed-parameter model (see Table 3). Contrarily, eight variables (motorcycle run-off crash, black helmet color, experienced rider course, motorcycle-specific shoes, height of rider, rider under the influence of depressant or multiple drugs, and no physical impairment involved) that were *statistically insignificant* at 90% in AIS-based model were indeed *statistically significant* in ISS-based models. This suggests at a naïve level that ISS-based models can have better explanatory power compared to AIS. As part of future work, we recommend an in-depth analysis of models based on AIS and ISS to get solid insights about explanatory and predictive leverage of the two injury scoring systems.

TABLE 4: Variance Covariance Matrices (Cholesky Matrices) for Uncorrelated Random Parameter Tobit (URPT), and Correlated Random Parameter Tobit (CRPT) Models

Uncorrelated random parameter tobit (URPT) Cholesky matrix						
	Distance indicator: Distance in feet between POI to POR (1 if > 9, 0 otherwise)	*Time indicator:* Time in seconds from precipitating event to impact (1 if > 2.3, 0 otherwise)	Half face motor vehicle, motorcycle helmet (1/0)	Acceptable helmet fit (1/0)	MC running off roadway, no OV involvement (1/0)	Positive BAC (1/0)
Distance in feet between POI to POR (1 if > 9, 0 otherwise)	13.37 [44.36]	0	0	0	0	0
Time indicator: Time in seconds from precipitating event to impact (1 if > 2.3, 0 otherwise)	0	11.42 [40.53]	0	0	0	0
Half face motor vehicle, motorcycle helmet (1/0)	0	0	9.62 [14.32]	0	0	0
Acceptable helmet fit (1/0)	0	0	0	4.48 [16.88]	0	0
MC running off roadway, no OV involvement (1/0)	0	0	0	0	23.42 [28.17]	0
Positive BAC (1/0)	0	0	0	0	0	18.27 [21.00]
Correlated random parameter Tobit (CRPT) Cholesky matrix						
Distance indicator: Distance in feet between POI to POR (1 if > 9, 0 otherwise)	15.03 [50.43] (1.00)	1.34 [5.13] (0.113)	0.10 [0.21] (0.014)	2.61 [10.45] (0.470)	-6.35 [-10.52] (-0.226)	24.12 [36.30] (0.758)
Time indicator: Time in seconds from precipitating event to impact (1 if > 2.3, 0 otherwise)	1.34 [5.13] (0.113)	11.77 [43.47] (1.00)	-7.37 [-14.28] (-0.982)	-0.87 [-3.88] (-0.102)	18.48 [27.09] (0.629)	-7.41 [-12.93] (-0.145)
Half face motor vehicle, motorcycle helmet (1/0)	0.10 [0.21] (0.014)	-7.37 [-14.28] (-0.982)	0.99 [2.06] (1.00)	4.82 [24.15] (0.278)	-7.40 [-12.93] (-0.692)	8.69 [14.29] (0.278)
Acceptable helmet fit (1/0)	2.61 [10.45] (0.470)	-0.87 [-3.88] (-0.102)	4.82 [24.15] (0.278)	0.23 [2.10] (1.00)	-10.21 [-17.78] (-0.454)	11.33 [18.18] (0.645)
MC running off roadway, no OV involvement (1/0)	-6.35 [-10.52] (-0.226)	18.48 [27.09] (0.629)	-7.40 [-12.93] (-0.692)	-10.21 [-17.78] (-0.454)	15.63 [26.66] (1.00)	-8.60 [-13.74] (-0.678)
Positive BAC (1/0)	24.12 [36.30] (0.758)	-7.41 [-12.93] (-0.145)	8.69 [14.29] (0.278)	11.33 [18.18] (0.645)	-8.60 [-13.74] (-0.678)	9.79 [17.50] (1.00)

Notes: t-statistics in brackets and correlation parameters between random parameters shown in parenthesis; POI is Point of Impact; POR is Point of Rest; MC is motorcycle; OV is other vehicle; BAC is Blood Alcohol Concentration.

4. DISCUSSION

The results and findings discussed here refer to the correlated random parameter Tobit model given its best fit among all competing models (Table 3). Overall, the corner-solution injury severity models quantify the associations between a wide variety of factors and the injury severity score of multiply injured rider. In the discussion of results, the word “crash” is used to refer to an injury crash. In interpreting the heterogeneity related findings presented next, note that some of the variability across the parameters may just reflect the fact that crashes in this study were a mixture of types and that some variables may have been relevant (or more relevant) for some types of crashes, e.g., multiple vehicle vs. single vehicle motorcycle crashes.

4.1. Rider’s Apparel and Visual Conspicuity

Several factors related to rider’s apparel and conspicuity are statistically significantly associated with the injury severity score, given a crash. While the correlations between motorcycle rider conspicuity and crash/injury risk have been examined (Wells et al. 2004), little to no information exists about how rider’s apparel may be correlated with the injuries sustained by a rider given a crash. Furthermore, as acknowledged in (Shaheed et al. 2013), conspicuity related factors (such as rider clothing, helmet color, etc.) are rarely observed in police-reported crash data. MCCS offers a unique opportunity to take a deeper look into how rider conspicuity and apparel relates to injury severity.

Related to rider apparel, our analysis reveals that if motorcyclist’s shoes are motorcycle-specific, the injury severity score on-average decreases by 5.95 units, after controlling for observed and unobserved factors (see negative parameter estimate in Table 3 and marginal effects in Table 5). This finding is important in that it highlights the efficacy of wearing proper motorcycle shoes especially when riders are typically less likely to wear motorcycle-specific shoes (de Rome 2006) at times when long-established trends of injury risk confirm that legs are the part of the body that are most likely to be injured in motorcycle crashes (de Rome 2006). Also, note that fixed-parameter Tobit model significantly underestimates the efficacy of motorcycle-specific shoes, i.e., a decrease of only 3.42 units in ISS for fixed parameter model compared to a decrease of 5.95 units in correlated random parameter model (see Table 5).[9,10]

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[9] We emphasize that the finding related to the effectiveness of motorcycle-specific shoes in preventing lower extremity (including legs) should be interpreted with some caution as our analysis did not look at injury by all the body regions. However, while we did not directly model the injury severity sustained by lower extremity (including legs), the dependent variable (ISS) can still reflect the injuries to lower extremity in cases where lower extremity was among the three most severely injured body regions. For the MCCS sample used in this study, the lower extremity was among the three most severely injured body regions for around 76% (N=245 riders) of all riders. As such, the ISS for these riders reflect the injuries sustained by lower extremities. Thus, while not a direct association, the finding that motorcycle-specific shoes were associated with lower ISS is likely tracking the potential reductions in injury severity sustained by lower extremity. At a next level, while not the key focus of the present study, we conducted additional analysis to gain a high-level insight into the direct correlation (if any) between motorcycle-specific shoes and injury severity sustained by lower extremity (as classified by AIS). As a rider can sustain multiple injuries on lower extremity, we only considered the maximum injury severity sustained by lower extremity and estimated a simple ordered probit model with the AIS-classified maximum injury severity sustained by lower extremity as the response outcome. For the 322 riders, 47 had no injury to lower extremity, whereas 171, 63, and 41 riders sustained minor, moderate, and serious/severe injuries, respectively. Motorcycle-specific shoes were found to be negatively correlated with injury outcomes to lower extremity ($\beta = -0.424$; p-value = 0.040). That is, if a rider wore motorcycle-specific shoes, the probability of no injury to lower extremity increased by 0.095 units whereas the probability of moderate and serious/severe injury decreased by 0.065 and 0.088 units, respectively. Though injuries by rider body parts should be conceptually and methodologically analyzed in more detail (see section 7), this finding further provides evidence in favor of the protective effect of motorcycle-specific shoes in preventing lower extremity injuries.

[10] From a behavioral perspective, an argument can be made that riders who wear motorcycle-specific shoes are likely to be more risk averse and safer. Thus, there is a possibility that our findings related to motorcycle-specific shoes may also be tracking risk aversion. However, some of the risk aversion is captured by the rigorous methodological framework used in the study. That is, this study accounts for unobserved factors (which includes risk aversion); therefore, any correlation found between observed factors (such as motorcycle-specific shoes) and injury severity score is likely the ‘true’ correlation.

In addition, motorcycle rider conspicuity, i.e., detectability and visibility on road, is regarded as a "high-priority" key risk factor in the US DOT's National Agenda for Motorcycle Safety (NHTSA 2013). A key finding from the famous Hurt Report was that "motorcycle riders with high conspicuity were less likely to have their right-of-way violated by other vehicles." (Hurt et al. 1981). To this effect, our analysis shows that if the upper body clothing was retroreflective (higher conspicuity), the injury severity score decreased by 1.89 units (see Table 5). In this case, the fixed parameter counterpart overestimates the effectiveness of retroreflective upper body clothing (see Table 5), highlighting the importance of accounting for correlated unobserved heterogeneity. Note that wearing retroreflective or fluorescent clothing is one key measure to enhance the rider's conspicuity (de Rome et al. 2011). We acknowledge that while lower visibility (lower conspicuity) of the rider can be more directly related to crash occurrence (Wali et al. 2018e), it can also be related to severity and in fact, increases the risk of motorcycle crash related injury (Wells et al. 2004). One possible reason for this is the potential reverse causality between rider visibility and response mechanisms of the crash-involved driver. For instance, a more visible rider (higher conspicuity) is more likely to be detected by a motorist and thus the driver may take evasive maneuvers to avoid a crash (or to decrease the impact of a crash) once he/she has already detected the rider. On the other hand, if a rider goes undetected (due to rider's low conspicuity especially at night), the chances are that the driver may not have the opportunity to undertake "necessary preventive maneuvers", resulting in a potentially higher impact collision, and a higher chance of a more severe injury. While this study focuses on injury outcomes, note that drivers slowing down more or being more cautious (potentially due to higher conspicuity of the rider) should also result in some potential crashes being avoided, thus lowering crash risk as well. In a recent MCCS-based crash propensity analysis, a positive association was found between lower conspicuity (as captured by dark (red) colored upper clothing) and crash propensity (Wali et al. 2018e). However, no statistically significant association was found between retroreflective upper body clothing and crash risk after controlling for other observed and unobserved factors (Wali et al. 2018e).

Related to the frontal color of rider's apparel, we found a statistically significant strong positive association between (dark) blue color waist down clothing and the injury severity score.[11] Referring to the marginal effects in Table 5 for correlated random parameter Tobit model, blue color waist down clothing on-average increased the injury severity score by 5.44 units, compared to only 1.31 units increase in fixed-parameter Tobit model (see Table 5). This again highlights the severe implications of failure to properly account for correlated unobserved heterogeneity in motorcycle injury severity analysis. The frontal color of clothing has also been investigated in the past. For instance, (Wells et al. 2004) found black and blue as the predominant colors for lower body clothing. However, no association was found between risk of crash related injury and frontal color of clothing (Wells et al. 2004).

Helmet color is also one of the factors that can increase or decrease rider conspicuity (Wells et al. 2004, Gershon et al. 2012). Usually, dark colored helmets (such as black) can decrease rider conspicuity whereas light colored helmets can increase conspicuity at times when the level of rider conspicuity can influence injury outcomes (as observed above in our findings and in relevant literature (Wells et al. 2004)). Our analysis shows that black colored helmets are associated with a significant increase in the injury severity score (an increase of 4.25 units – see Table 5), whereas light colored helmets (such as silver or grey) are found associated with a significant decrease in the injury severity score (a decrease of 7.56 units). These findings are in agreement with those of Wells et al. (2004) and are important and intuitive as usually dark colored helmets (such as black) can decrease rider conspicuity (especially at night) thus increasing the risk of injury (Wells et al. 2004). Interestingly, our analysis shows that white colored helmets are also

[11] Note that the color of clothing variable may also be tracking the body protection offered by different types of clothing. Thus, the results related to frontal color of rider's apparel may not be solely reflecting the disutility of lower conspicuity and can be a mix of the effects of lower conspicuity of lower body clothing and the level of protection offered by specific types of lower body clothing. For instance, dark blue color clothing on lower body may be relevant to jeans apparel (often blue) providing less protection than leather (almost always black), rather than being related to conspicuity.

associated with a significant increase in the injury severity score, given a crash (see Table 3). This finding may seem apparently unintuitive as white colored helmets are usually believed to increase rider conspicuity and thus lower risk of injury. However, note that a white outfit (such as a white helmet) may increase conspicuity in a more complex and multi-colored urban environment, whereas, it can, in fact, decrease rider's conspicuity where a background is solely a bright sky (such as on inter-urban roads) (Gershon et al. 2012). Methodologically, ignoring correlated unobserved heterogeneity can lead to marked differences in the estimated marginal effects of key risk factors on the injury severity score (see differences in marginal effects between fixed parameter Tobit and correlated random parameter Tobit model in Table 5).

4.2. Helmet Coverage, Rider's Experience and Alcohol/Drugs

The statistical models also quantify the associations in crashes between the type of helmet coverage, rider experience, use of alcohol or multiple drugs, and the injury severity score. It is found that helmets with partial coverage (Half face motor vehicle, motorcycle helmets) are associated with an increase in the injury severity score (Table 5). Such helmets are US DOT compliant helmets with partial coverage, and least intrusive covering only the top half of the cranium. This finding is intuitive as such helmets provide less coverage compared to full face helmets and thus a higher risk of injury. However, note that this variable is found to be normally distributed random parameter suggesting that the effects of this variable vary significantly across observations. For instance, with a mean of 5.31 and standard deviation of 7.45 (refer to CRPT model in Table 3), the associations between partial coverage helmets and the injury severity score are positive for 76.2% of the observations and negative for the rest. Likewise, a rider with an acceptable helmet fit significantly decreased the injury severity score by 8.81 units (Table 5). These findings are in agreement with previous research where poor helmet fit is reported to be a key risk factor associated with risk of injury (Rivara et al. 1999). However, we also found that the associations between acceptable helmet fit and the injury severity score are significantly heterogeneous in magnitudes with negative associations for 94.3% of the observations and positive associations for the rest (Table 3). While the estimates from fixed and random parameter models differ significantly, it is also important to mention that failure to account for correlated unobserved heterogeneity can also lead to inaccurate parameter estimates – see the differences in parameter estimates from URPT and CRPT in Table 3.

Related to rider experience related factors, it is found that if a rider had gaps in between their riding, they are more likely to sustain severe injuries. Contrarily, if a rider had experienced rider course, their injury severity score on-average decreased by 8.20 units, compared to a 6.95-unit decrease indicated by the fixed parameter Tobit model (see Table 5). Again, these findings are intuitive as more experienced riders can better respond and handle the motorcycle in unsafe situations.

Importantly, from a behavioral standpoint, a positive Blood Alcohol Concentration (BAC) is found associated with a significant increase of 15.61 units in the injury severity score as per best-fit correlated random parameter Tobit model, compared to an increase of only 7.09 and 2.75 units indicated by fixed parameter and uncorrelated random parameter Tobit models (see Table 5). This finding is very important as it indicates the severe consequences of riding under the influence of alcohol. Again, the parameter estimates for this variable are found to normally distributed random parameters suggesting that the associations vary significantly across sampled crashes. Likewise, if a rider has taken depressant or multiple drugs, their injury severity score increased statistically significantly (see Table 3).

All of the above findings relate to "policy-sensitive" and "preventable" key risk factors. For instance, by encouraging riders to increase their conspicuity and/or by using motorcycle-specific rider clothing, a reduction in motorcycle crashes can be achieved. Likewise, through experience enhancing programs and strategies for reduction in riding under the influence of alcohol, significant gains can be obtained in the shape of reducing harm from a motorcycle crash.

4.3. Rider and Crash Specific Factors

The estimation results shed light on the associations between several important rider and crash-specific factors and their injury severity scores. Regarding rider-specific factors, the results show that age of a rider is positively correlated with the injury severity score, i.e., a one-unit increase in rider's age increases the injury severity score by 0.02 units (see Table 5). That is, compared to younger riders, old riders are more likely to sustain severe injuries given a crash. This finding is intuitive as not only older riders are more prone to receiving injuries due to physical characteristics but also age is an independent predictor of survival following a trauma (Bergeron et al. 2004). Likewise, the height of rider and the injury severity score (ISS) sustained by a rider are negatively correlated with a 1.67 decrease in ISS with a one-foot increase in height of a rider. Again, the marginal effects obtained from fixed parameter Tobit and URPT models differ significantly than the best-fit CRPT model (see Table 5). Finally, if a rider has no physical impairment or if the rider has black ethnicity, the ISS intuitively decreases by 2.96 and 5.91 units respectively[12] (Table 5).

Related to crash-specific factors, the estimation results show that travel speed before a crash is statistically significantly positively associated with ISS. A one-unit increase in speed increases ISS by 0.27 units. The MCCS also provides unique information about the distance between the rider's point of impact (POI) and the rider's point of rest (POR). Likewise, information is available about the time in seconds from the precipitating event to impact where the precipitating event is the event that majorly led to the crash occurrence. The results suggest that if riders had more than 2.3 seconds between the precipitating event and impact, their ISS on-average increased by 3.06 units (Table 5). Whereas, if the riders at least 9 feet distance covered from their point of impact to their point of rest, their ISS on-average increased by 1.29 units despite significant heterogeneity in the magnitudes of associations (Table 3). Both variables are found to be normally distributed random parameters suggesting that the associations between these variables and ISS do not only vary in magnitude but also in direction. Related to the manner of collision, if the motorcycle run off the roadway with no other vehicle involvement, the ISS increased by 5.58 units (Table 5). However, the positive association was observed only for 57.89% of observations as indicated by the normal distribution with a mean of 5.58 and standard deviation of 28.03 (see parameter estimates for this variable from CRPT model in Table 3). Finally, related to geometric features, crashes on curves with a constant speed were associated with lower ISS, whereas riders who crashed on two-way undivided highways and level grades were associated with greater injury severity scores, respectively (Table 5).

4.4. Interpretation of Correlated Random Parameters

Accounting for unrestricted correlations among random parameters can provide deeper insights regarding the combined interacting effects of key risk factors on injury severity scores. Note that the estimated correlations shown in Table 4 (enclosed in parenthesis) reflect the correlations among the unobserved factors captured through the random parameters and are not simple Pearson (linear) correlations between corresponding independent variables. An examination of the potential correlations between random parameters in terms of unobserved factors can provide deeper insights regarding the interactive effect of motorcycle-crash specific variations as it relates to injuries sustained by the rider and provides suggestions

[12] In the vehicle injury severity literature, driver race is known to be one of the important determinants of injury outcomes, given a crash (Tay and Rifaat 2007). For instance, Tay and Rifaat (2007) found that crashes were more severe when they involved foreign drivers (compared to Chinese drivers) both at signalized and unsignalized intersections in Singapore (Tay and Rifaat 2007). Likewise, compared to white group, racial groups (black, Hispanic, etc.) were found to have significantly lower risk of mortality and severe/very severe injuries (Cummins et al. 2011). Note that ethnicity/race of a driver can directly or indirectly be correlated with injury severity. For example, a specific group of drivers/riders may exhibit more risk-taking behavior (such as non-usage of seatbelts by drivers or speeding behavior by riders) in general and thus can be severely injured given a crash. Likewise, some ethnic groups on average may exhibit stronger physical characteristics and thus can be less prone to trauma given a crash. As a result, we also tested ethnicity related variables in our analysis.

as to what possible unobserved factors are commonly shared among the pairs of the random parameters. Referring to the interactions between random parameters, the lower panel of Table 4 reveals a positive correlation (the correlation coefficient is 0.758) between the unobserved factors varying systematically among the cases with distance indicator (distance in feet between point of impact to point of rest greater than 9 feet) and positive blood alcohol concentration (BAC) indicator. This suggests that the interaction (in terms of unobserved heterogeneity) of these two parameters has a positive effect on the injury severity score. Importantly, this suggests that not just both random parameters (positive BAC and distance indicator) significantly increase injury severity scores, but the interaction between unobserved factors associated with positive BAC and distance indicator increase the injury severity score as well (as reflected in a correlation coefficient of 0.758). This also reveals that a good proportion of unobserved factors characterizing the variations in the effects of positive BAC and distance indicator are common between this pair of random parameters. Likewise, a positive correlation of 0.278 between the positive BAC indicator and partial helmet coverage indicator suggests that the systematic variations of the unobserved factors among cases with these two indicator variables are positively correlated with the injury severity score (Table 4), and that the effect of unobserved heterogeneity interactions specific to these two variables is in line with the effects of their individual random parameters (see strong positive parameter estimates in Table 3). On the contrary, despite that random parameters related to motorcycle running off roadway (with no other vehicle involvement) and distance indicator both increase the ISS (see the positive parameter estimates in Table 3), the unobserved heterogeneity interaction specific to these two variables (in terms of interactions between the unobserved factors) is associated with a lower injury severity score, as indicated by the correlation coefficient of -0.226 (Table 4). This negative correlation between the unobserved factors associated with distance indicator and motorcycle running off roadway reveal their mixed effects on the rider injury severity mechanism, i.e., the unobserved factors characterizing the variations in the effects of the distance indicator and the motorcycle running off the roadway possibly have a counterbalancing effect across the motorcycle crash observations. Finally, the unobserved factors associated with acceptable helmet fit and motorcycle running off roadway are negatively correlated (correlation coefficient of -0.454), which is intuitive since with acceptable helmet fit the negative consequences of motorcycle running off roadway (in terms of increasing injury severity) could be alleviated, at least preventing some injuries to head as compared to head injuries sustained by a rider who runs off the roadway wearing a helmet with a non-acceptable fit. The interactive effects of other correlated random parameters on the injury severity score can be interpreted similarly. As is evident, accounting for the potential correlations between the random parameters improves our understanding of the complex associations of key risk factors (and the underlying unobserved factors) with injury severity scores.

TABLE 5: Marginal Effects of Fixed Parameter Tobit, URPT, and Best-Fit CRPT Models

	Fixed Parameter Tobit			Uncorrelated Random Parameter Tobit			Correlated Random Parameter Tobit		
Variables	**ME-1**	**ME-2**	**ME-3**	**ME-1**	**ME-2**	**ME-3**	**ME-1**	**ME-2**	**ME-3**
Rider Apparel & Conspicuity Related Factors									
Upper body clothing retroreflective (1/0)	-2.58	-9.40%	-1.81	-2.04	-0.91%	-1.98	-1.89	-0.02%	-1.89
Shoes MC specific (1/0)	-3.42	-12.46%	-2.40	-5.58	-2.49%	-5.42	-5.95	-0.08%	-5.94
Upper clothing MC specific (1/0)	4.03	14.68%	2.83	4.40	1.96%	4.27	3.21	0.04%	3.21
Blue color waist down clothing (1/0)	1.33	4.83%	0.93	5.30	2.36%	5.14	5.45	0.07%	5.44
Helmet color (multicolor)	13.18	48.00%	9.26	15.40	6.86%	14.94	17.02	0.22%	17.01
Helmet color (White)	11.54	42.04%	8.11	9.65	4.30%	9.36	9.85	0.13%	9.84
Helmet color (silver, grey)	-3.74	-13.60%	-2.62	-7.74	-3.45%	-7.51	-7.56	-0.10%	-7.55
Helmet color (Black)	4.87	17.74%	3.42	5.44	2.42%	5.28	4.25	0.05%	4.25
Rider Experience Related Factors									
Gap exists between riding (1/0)	1.52	5.52%	1.07	4.12	1.83%	4.00	3.39	0.04%	3.39
Experienced rider course (1/0)	-7.00	-25.49%	-4.92	-7.69	-3.42%	-7.46	-8.21	-0.11%	-8.20
Helmet Related Factors									
Half face motor vehicle, motorcycle helmet (1/0)	4.10	14.91%	2.88	4.87	2.17%	4.72	5.31	0.07%	5.31
Acceptable helmet fit (1/0)	-5.93	-21.61%	-4.17	-9.56	-4.25%	-9.27	-8.82	-0.11%	-8.81
Alcohol/Drugs Intake									
Positive BAC (1/0)	7.14	26.00%	5.02	2.76	1.23%	2.67	15.62	0.20%	15.61
Rider took depressant or multiple drugs (1/0)	5.52	20.10%	3.88	2.99	1.33%	2.90	2.30	0.03%	2.30
Rider Specific Factors									
Height of rider	-4.55	-16.58%	-3.20	-3.68	-1.64%	-3.57	-1.68	-0.02%	-1.67
Age of rider at time of crash (years)	0.05	0.16%	0.03	0.04	0.02%	0.04	0.03	0.001%	0.03
Rider has no physical impairment (1/0)	-3.52	-12.83%	-2.48	-3.70	-1.65%	-3.59	-2.96	-0.04%	-2.96
Ethnicity: Black rider (1/0)	-2.63	-9.57%	-1.85	-5.86	-2.61%	-5.68	-5.92	-0.08%	-5.92
Crash Specific Factors									
Travel speed before crash (mph)	0.21	0.76%	0.15	0.29	0.13%	0.28	0.28	0.004%	0.28
Time in seconds from precipitating event to impact (1 if > 2.3, 0 otherwise)	4.29	15.63%	3.01	2.35	1.05%	2.28	3.07	0.04%	3.06
Distance in feet between POI to POR (1 if > 9, 0 otherwise)	2.45	8.91%	1.72	4.08	1.82%	3.96	1.30	0.02%	1.29
Negotiating a curve, constant speed (1/0)	-4.38	-15.93%	-3.07	-4.67	-2.08%	-4.53	-2.89	-0.04%	-2.89
Two-way undivided highway (1/0)	1.54	5.61%	1.08	4.18	1.86%	4.06	4.65	0.06%	4.64
Level grade (1/0)	3.27	11.89%	2.29	4.08	1.82%	3.96	3.92	0.05%	3.91
MC running off roadway, no OV involvement (1/0)	5.48	19.96%	3.85	7.32	3.26%	7.10	5.58	0.07%	5.58

Notes: (*) MC is motorcycle; POI is Point of Impact; POR is Point of Rest; OV is other vehicle; BAC is Blood Alcohol Concentration; ME-1, ME-2, and ME-3 show the effect of a unit change in explanatory factor on the expected value of censored and uncensored ISS (Equation 14), on the probability of being uncensored (Equation 15), and on the expected value of uncensored ISS outcomes (Equation 12) respectively; ME-1 and ME-2 show the increase/decrease in ISS with a unit change in explanatory factor;

ME-3 shows the “percent change” in the probability of being uncensored with a unit change in a predictor.

5. LIMITATIONS

The present study is based on a sample of 321 injury crash events in Orange County, California. This study uses MCCS data, which is the most comprehensive national effort to-date. However, the sampled crashes may not be representative of the national population. Second, the data collected in MCCS are retrospective in nature. That is, the study framework looks backward and investigates the key causes of a crash. As such, retrospective studies may be exposed to errors related to confounding and bias. However, as the investigations in this study are performed in the field by trained experts, and do not build on investigator’s memory per se, the extent of confounding and recall bias is likely small. Also, while the MCCS is an extensive database, deeper information is missing in some cases especially on riding behavior. For instance, the dataset used in this study did not contain information about why there was a gap in riding. The implication of this can be that if the gap occurred because of being involved in a crash or near-miss, then this could also affect the riding style, e.g., see the potential “deterrence effects” as discussed in a related study (Wali et al. 2018e). Thus, the gap in the riding variable (as is used in this study) is not the most accurate marker of potential skill decay. Finally, the federally-funded MCCS by design includes non-fatal injury crashes only. Thus, the key findings presented in this study are only relevant to injury crashes and as such cannot be generalized to crashed but uninjured or fatally injured riders. However, most of the motorcycle involved crashes in 2015 resulted in injuries. According to National Highway Traffic Safety Administration (NHTSA) (NHTSA 2015), a total of 102,131 motorcycle crashes occurred in the U.S. in 2015, out of which 5,131 (5.02%) were fatal crashes, 84,000 (82.25%) were non-fatal injury crashes, and only 13,000 (12.73%) were property damage only crashes (PDO). Thus, MCCS data represents non-fatal injury crashes, which are most of such crashes in the U.S.

6. CONCLUSIONS

The key objective of this study was to examine how different “high-priority” key risk factors correlate with the injury severity sustained by motorcycle rider given a crash. A comprehensive search was conducted to capture existing work and describe as well as synthesize it. The study contributes by: (i) investigating how rider experience, apparel type and conspicuity relate to motorcycle injury severity outcomes; (ii) quantifying the relationships between helmet type and coverage, rider-specific characteristics (alcohol and drug intake, rider age, physical impairment, etc.) and injury severity outcomes; and (iii) applying a methodologically rigorous framework that fully accounts for uncorrelated and correlated unobserved heterogeneity. The analysis is based on data from a comprehensive US DOT Federal Highway Administration’s Motorcycle Crash Causation Study (MCCS), where 351 motorcycle-involved injury crashes are analyzed. Compared to analysis based on traditional police-reported crashes through injury severity measures such as KABCO and/or Abbreviated Injury Scale (AIS), the present study took a unique approach by analyzing an anatomical injury severity scoring system, termed as the Injury Severity Score (ISS), that provided an overall score by accounting for the possibility of multiple injuries to different body parts of a rider, given a crash.

The study employed a Tobit modeling framework in a corner-solution setting in order to account for the left-tail spike in the distribution of injury severity scores. Unlike traditional fixed parameter Tobit models, a fully flexible random parameter Tobit modeling framework is employed which accounted for the possibility of heterogeneous effects of exogenous factors due to systematic variations in unobserved factors. Compared to the standard random parameter modeling framework, the empirical analysis presented in this paper also accounts for uncorrelated as well as correlated unobserved heterogeneity in the effects of exogenous factors on injury severity scores. Correlated random parameter Tobit model provided the best-fit, and significantly outperformed the uncorrelated random parameter Tobit and the fixed parameter Tobit models. From an empirical standpoint, the findings suggest the presence of significantly correlated heterogeneity in the effects of exogenous factors on injury severity scores, and that ignoring correlated unobserved heterogeneity can lead to inaccurate estimates and erroneous inferences.

Overall, the model estimation results indicate that several high-priority key risk factors exhibit heterogeneous and mixed effects (in terms of direction of effect) on the injury severity score given a crash. This is an important finding, as it indicates that a key risk factor can affect injury severity scores in different ways. This inference is further supported by the correlations among the random parameters, i.e., how the interactions between random parameters may affect the injury severity score. That is, not only do the individual effects of random parameters vary significantly across observations, but the interactions between unobserved factors characterizing random parameters significantly influence injury severity scores as well. We also observed that the combined effect of the correlated random parameters differed from the equivalent separate effects under the uncorrelated random parameter Tobit model. The study methodologically contributes by applying rigorous simulation-assisted inference-based frequentist modeling approaches to address uncorrelated and correlated unobserved heterogeneity in a Tobit modeling framework. Also, the study goes beyond the standard practice in the literature by estimating the statistical significance of standard deviations of correlated random parameters, and which is not done usually in the practice of application of correlated random parameter technique. The data and methods are discussed in enough detail that others can potentially replicate it.

Several important findings surfaced from the empirical analysis. Regarding rider apparel type and conspicuity, we found that if motorcyclist's shoes were motorcycle-specific, injury severity scores decreased significantly by 5.94 units. Likewise, if the rider's upper body clothing was retroreflective, injury severity scores decreased significantly. Compared to previous research, we found a statistically significant positive association between the frontal color of rider's apparel and the injury severity score (ISS), with (dark) blue color waist down clothing positively correlated with ISS. Given the comprehensive nature of MCCS, our analysis also allowed examining correlations between helmet color and ISS. We found that black colored helmets are associated with a significant increase in ISS, whereas, light colored helmets (such as silver or grey) are correlated with a significant decrease in ISS. All of these findings relate to "policy-sensitive" and "preventable" key risk factors. The conclusions are that reductions in injury severity are possible by increasing rider conspicuity and/or by using motorcycle-specific lower clothing.

Related to helmet coverage, our analysis suggests that helmets with partial coverage (Half face motor vehicle, motorcycle helmets) are associated with an increase in injury severity scores. Contrarily, riders with acceptable helmet fit on-average experienced lower injuries given a crash. Regarding rider experience related factors, it is found that if a rider had gaps in between their riding, they are more likely to sustain severe injuries. Contrarily, if a rider had taken experienced rider course, their injury severity score on-average decreased. Importantly, from a behavioral standpoint, a positive Blood Alcohol Concentration (BAC) is found to be associated with a significant increase of 15.61 units in injury severity scores as per best-fit correlated random parameter Tobit model. This finding is very important as it indicates the severe consequences of riding under the influence of alcohol. Likewise, if a rider has taken depressant or multiple drugs, their injury severity score increased statistically significantly. All of the above findings relate to "policy-sensitive" key risk factors. For instance, through experience enhancing programs and strategies for reduction in riding under the influence of alcohol, significant gains can be obtained in the shape of reducing harm from a motorcycle crash. The analysis also quantified associations between several riders and crash specific factors and injury severity scores. For instance, both rider age and travel speed are positively associated with injury severity scores, whereas, the height of a rider is negatively correlated with injury outcomes. While the study does not advocate for specific government policies, we are optimistic that the findings provide information that can help formulate countermeasures and future policies.

7. FUTURE DIRECTIONS

The present study identifies several interesting research directions that can be pursued in future research. Methodologically, the current results indicate the statistical supremacy of correlated random parameter Tobit model compared to the uncorrelated random parameter and the fixed parameter counterpart. Any other potential improvements of the models, such as consideration of the spatial and temporal effects and their interactions, can further provide important insights into the spatiotemporal mechanisms determining motorcyclist injury outcomes. We also recall that random (unobserved heterogeneity) is explicitly accounted for in the analysis, whereas, systematic heterogeneity (e.g., due to non-linearity) is not comprehensively covered. As future work, we recommend that both systematic and random heterogeneity components are simultaneously explored in injury severity score modeling. Without explicitly accounting for both systematic and random heterogeneity, it is impossible to discern the true source of heterogeneity (systematic or random) (Wali et al. 2018b). This is an important future direction since most of the heterogeneity-based safety literature focuses on tracking unobserved heterogeneity, at times when the specification requirement of the regression function requires adequate sensitivity to the linearity assumption. While we did not find statistically significant non-linear dependencies for key covariates (based on categorization of continuous variables, use of categorical variables, and use of U-shaped or high-order polynomial curves for variables such as rider's age), the data nonetheless exhibits complex non-linear contours that cannot be captured through standard methods such as polynomial models[13]. To this effect, it will be worthwhile to examine non-linear dependencies (in addition to accounting for random heterogeneity) through more advanced treatments (such as mixed Additive or Quantile models). We, however, acknowledge that some portion of the unobserved heterogeneity can potentially be characterized as a function of observed variables. Building upon the existing study, this will translate to modeling the distributional parameters of random parameters (such as mean and variance in case of normally distributed random parameters) as a function of observed factors (Behnood and Mannering 2017b, Behnood and Mannering 2017a, Wali et al. 2018e), potentially unveiling valuable information.

Using ISS, the present study analyzed injury severity of the three most severely injured ISS body regions. An alternative approach can be to simultaneously model the injury severities (as recorded through KABCO or AIS scale) sustained by different body parts of the rider while accounting for possibility of heterogeneous relationships, e.g., in an empirical framework similar to (Wali et al. 2018a, Wali et al. 2018f) (Eluru et al. 2010, Russo et al. 2014, Boakye et al. 2018). Also, note that the current study focuses on modeling the injury severity score of crash-involved rider. In the future, depending on data availability, injury severity scores of riders as well as passengers, and/or drivers of crash-involved vehicles can be simultaneously modeled. In this case, a multivariate Tobit framework with correlated heterogeneity can be employed, e.g., see (Anastasopoulos 2016). From an injury measurement perspective, ISS considers lower and upper extremity together, whereas, AIS codes Upper Extremity and Lower Extremity as different regions. This implies that riders with multiple injuries (some of which are upper and some of which are lower extremity) are coded as if they have single injuries under ISS. In case of multiple injuries to Extremities or pelvic girdle (some of which are upper and some of which are lower extremity), ISS will only consider the most-severe injury as classified by AIS and not the other injuries sustained by the same ISS body region. While ISS quantifies the impact of "multiple injuries" on mortality, it does not account for multiple injuries (some of which can be upper and some which can be lower) within same ISS body region (such as Extremities or pelvic girdle). This is a widely recognized limitation of ISS. The New Injury Severity Score (NISS) and Anatomic Profile (AP) measures can overcome these limitations. For instance, NISS scores the three most severe AIS scores regardless of their body region location. Thus, multiple severe injuries within a body region (such as Extremities or pelvic girdle) can be considered in the NISS or in AP. As part of a future study, it will be interesting to compare ISS, NISS, and AP in terms of their potential to better predict injury severities sustained by a rider[14]. Finally, connected and automated vehicle technology

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[13] For instance, it could be argued from other research that perhaps injury severity might be highest in the youngest and oldest groups, rather than linearly changing with age (Abdel-Aty et al. 1998, Newgard 2008). To this effect, U-shaped, quadratic, or higher order polynomials can be used to better track non-linearities. While not the focus of the current paper, we performed a careful analysis to see if a U-shaped relationship holds for rider's age. For this specific data, the analysis revealed that a 2nd order U-shaped curve, or higher order polynomials, do not hold for the age variable and are in fact statistically inferior to a linear fit in terms of goodness of fit (the BIC statistics for 2nd, 3rd, and 4th order polynomial model for age were higher than the BIC statistic for a simple model with age as a linear predictor). However, note that this does not necessarily indicate absence of non-linearities rather it suggests that simpler non-linear models are not able to track the complex contours in this data, especially when a scatter plot of ISS vs. rider age (not shown here) revealed a complicated relationship.

[14] The authors are currently pursuing research efforts along these lines, and to examine and simultaneously analyze injury severities sustained by a rider at body parts level.

can have significant implications for vulnerable road user safety. Thus, it will be interesting to examine, in a simulation-based or ideally an empirical setup, how patterns and outcomes of motorcycle crashes will evolve as connected and automated vehicles technologies penetrate our transportation network (Fagnant and Kockelman 2015, Arvin et al. 2018).

8. ACKNOWLEDGEMENT

This paper is based on work supported by the US Department of Transportation through the Collaborative Sciences Center for Road Safety (CSCRS), a consortium led by The University of North Carolina at Chapel Hill (UNC) in partnership with The University of Tennessee. The title of the on-going research project (R-20) is “Investigating the Vulnerability of Motorcyclists to Crashes and Injury.” The data for this study were provided by the Federal Highway Administration (FHWA). The assistance of Ms. Carol Tan and Mr. Yusuf Mohamedshah is highly appreciated. The contribution of Zachary Jerome in terms of proof-reading and paper editing is greatly appreciated.

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