Collaborative Sciences Center for ROAD SAFETY

FINAL REPORT

Investigating the Vulnerability of Motorcyclists to Crashes and Injury

November 30, 2020

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U.S. DOT Disclaimer

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16. Abstract
Motorcyclists represent a segment of vulnerable road users that have high levels of risk, mostly because they lack protection. There are about 5,000 motorcyclist fatalities every year in the US. In response, the U.S. Congress has passed legislation initiating comprehensive research that identifies the causes of motorcycle crashes. This in turn resulted in a new federally collected Motorcycle Crash Causation Study (MCCS) data. This project uses MCCS to conduct research and generate new knowledge about motorcycle safety. The key objectives of this project are to investigate motorcycle crash risk factors, e.g., how visual conspicuity (bright-colored or reflective clothing) influences riders' likelihood of being involved in a crash; and explore factors, e.g., types of helmets that correlate with severity of injuries, given a crash. Rigorous statistical analysis models that capture unobserved heterogeneity are used in this study. The results indicate that the risk of injury crash is significantly higher for riders lacking conspicuity. Crash risk was lower for riders who had recently received training. While partial helmet coverage was associated with lower crash risk, given a crash, they were associated with higher injury severity. The Injury Severity Score (ISS), given a crash provided deeper insights about the nature of injuries and showed that properly fitting helmets were positively correlated with lower injury severity. The implications of the findings are discussed in each chapter.

17. Key Words
Motorcyclists; Visual Conspicuity; Injury Crash; Injury Severity Score; Unobserved Heterogeneity; Case-Control, Tobit

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1. Introduction

Overview

Motorcyclists represent a segment of vulnerable road users that have very high levels of risk, mostly because they lack protection. Recently, the number of fatalities and severe injuries among vulnerable road users has risen. In the United States, 257 more motorcyclist fatalities occurred in 2016 than 2015, a 5.1% increase. Furthermore, the 2016 motorcyclist fatality count of 5,286 has been the highest since 2008 (NHTSA 2017). After accounting for vehicle miles traveled, motorcyclists are fatally injured 25 to 30 times more frequently than passenger vehicle occupants. Because of this expanding concern, the United States Congress has recently passed legislation initiating comprehensive research identifying the causes of motorcycle crashes (NHTSA 2017). This project focuses on a unique database of motorcycle crashes, the federally collected Motorcycle Crash Causation Study (MCCS), to explore the role of demographics and how key risk factors vary from one context to another, i.e., the settings in which motorcycle travel takes place. This project harnesses value from the new MCCS data and conducts cutting-edge research that generates knowledge about vulnerable road users, specifically motorcyclists. The project addresses four critical safety issues related to motorcyclists:

- Motorcycle crash risk factors, especially how visual conspicuity (bright-colored or reflective clothing) influences their likelihood of being involved in a crash
- How the frequency and causes of crashes among young and inexperienced riders differ from those of older, experienced riders
- How training & education programs relate to crash outcomes
- New automation technologies that can reduce identified risks in motorcycle crashes based on analysis of motorcycle crash risk factors

This study conducts a rigorous heterogeneity-based case-control analysis to account for both within and between matched case-control variations. Furthermore, the project explores how ignoring important methodological issues such as omitted variable biases and unobserved heterogeneity can influence the magnitude of relative risks (or odds ratios) and final inferences. The project also 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. An anatomical injury severity scoring system, termed Injury Severity Score (ISS), accounts for multiple injuries to different body parts of a rider. Note that ISS is not used very commonly in the transportation safety literature. It is based on the Abbreviated Injury Scale (AIS) and is calculated using $ISS = X^2 + Y^2 + Z^2$, where X, Y, and Z are the AIS scores of the three most severely injured body regions out of six body regions (Stevenson et al., 2001; Wali et al., 2019). Compared with the commonly used KABCO or AIS scales, ISS is an established medical scoring system used for assessing trauma severity and correlates with mortality, morbidity, and hospitalization duration after trauma (Stevenson et al., 2001). For modeling, fixed and random parameter Tobit modeling frameworks in corner-solution settings account for the left-tail spike in the distribution of ISS and for unobserved heterogeneity. Additionally, the developed random parameters Tobit framework accounts for the interactive effects of key risk factors, allowing for possible observed correlations among random parameters. The study applies rigorous statistical tools to explore key factors contributing to injury crash risks as well as motorcyclist injuries. The purpose is to enhance motorcyclists’ safety – one of the vulnerable road user groups.

Research questions

To improve road safety outcomes for motorcyclists, this project addresses seven research questions:

1. While controlling for rider-specific, psycho-physiological, and other observed/unobserved factors, how are different risk factors associated with motorcycle crash occurrence and injury severity?
2. How does motorcyclist conspicuity relate to crash risk?
3. How can ignoring important methodological issues such as omitted variable biases and unobserved heterogeneity influence the magnitude of relative risks (or odds ratios) and final inferences?
4. How does age and inexperience contribute to motorcycle crash outcomes and occurrences?
5. How do training & education programs impact crash outcomes?

6. How can automation eliminate errors associated with motorcycle crashes?
7. While using a different scoring system to measure injury severity and controlling for rider and crash specific factors as well as other observed/unobserved factors, how do different "policy-sensitive" factors correlate with injury severity?

Multi-pronged approach

This report describes work performed in several distinct efforts for this project. Each effort is listed under its own chapter heading:

Chapter 2. "Heterogeneity Based Case-Control Analysis of Motorcyclist's Injury Crashes: Evidence from Motorcycle Crash Causation Study" quantifies how different "policy-sensitive" factors are associated with motorcycle injury crash risk while controlling for rider-specific, psycho-physiological, and other observed/unobserved factors. This study utilizes a match case-control design collected through the Federal Highway Administration's (FHWA) Motorcycle Crash Causation Study (MCCS). Unlike traditional conditional estimation of relative risks, the paper presents heterogeneity based statistical analysis that accounts for both within and between matched case-control variations. The study investigates how rider conspicuity and amounts of sleep relate to injury crash risks. A rigorous heterogeneity based statistical model accounts for unobserved factors. This chapter discusses the findings related to key risk factors and unobserved heterogeneity.

Chapter 3. "Modeling Injury Severity Score as a More Precise Measure of Motorcyclist Injuries: A Correlated Random Parameter Corner Solution Framework" explores how different "policy-sensitive" factors correlate with injury severity while controlling for rider and crash specific factors as well as other observed/unobserved factors. This study analyzes 321 motorcycle injury crashes from the comprehensive US DOT FHWA's MCCS. An anatomical injury severity scoring system, termed as the Injury Severity Score (ISS), provides an overall score by accounting for multiple injuries to different body parts of a rider. Both fixed and random parameter Tobit modeling frameworks in corner-solution settings account for a left-tail spike in the distribution of ISS and for unobserved heterogeneity. The key findings of this study are briefly discussed in this chapter.

The aforementioned studies provide an opportunity to better understand research issues related to motorcycle injury crash risk and associated injury severity. These studies explore how "policy-sensitive" factors, rider conspicuity, and motorcycle-oriented clothing relate to both injury crash risk and injury severity. Also, this project tries to quantify the impact of a rider's training and age on crash risk.

Research outputs

Publications and Presentations

Wali, B., Khattak, A. J., & Khattak, A. J. (2018). A heterogeneity-based case-control analysis of motorcyclist's injury crashes: Evidence from motorcycle crash causation study. *Accident Analysis & Prevention*, 119, 202-214.

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.

Wali, B., Khattak, A. J., & Ahmad, N. (2019). Modeling Injury Severity Score as a More Precise Measure of Motorcyclist Injuries: A Correlated Random Parameter Corner Solution Framework, Paper No. 19-05185, Presented at *Transportation Research Board Annual Meeting*, National Academies, Washington, D.C., 2019.

Wali, B., Khattak, A. J., Khattak, A. J., & Ahmad, N. (2019). A heterogeneity-based case-control analysis of motorcyclist's injury crashes: Evidence from motorcycle crash causation study, Paper No. 19-05159, Presented at Transportation Research Board Annual Meeting, National Academies, Washington, D.C., 2019.

2. A Heterogeneity Based Case-Control Analysis of Motorcyclist's Injury Crashes: Evidence from Motorcycle Crash Causation Study

Authors

Behram Wali[1], Asad J. Khattak[1], Aemal J. Khattak[2], Numan Ahmad[1]

This chapter presents a brief version of a refereed journal paper on motorcycle crashes. The research was 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 in partnership with The University of Tennessee. A paper with the same title was presented at the 98th Annual Meeting of the Transportation Research Board. The paper was published in a transportation safety journal titled *Accident Analysis & Prevention* and is available online.

Access the paper at: https://www.sciencedirect.com/science/article/abs/pii/S0001457518303245.

Abstract

The main objective of this research is to quantify how different "policy-sensitive" factors, i.e., risk factors that can be mitigated through interventions such as training, conspicuity, and using motorcycle-oriented rider clothing, are associated with motorcycle injury crash risk while controlling for rider-specific, psycho-physiological, and other observed/unobserved factors. This study utilizes a match case-control design collected through the Federal Highway Administration's (FHWA) Motorcycle Crash Causation Study (MCCS). It analyzes 351 cases of motorcyclists involved in injury crashes vis-à-vis similarly-at-risk 702 matched controls (motorcyclists not involved in crashes). Unlike traditional conditional estimation of relative risks, the paper presents heterogeneity based statistical analysis that accounts for both within and between matched case-control variations. The results of the best-fit random parameters logit model with heterogeneity-in-means shows that riders with partial helmet coverage have significantly lower risk of injury crash involvement. Lack of motorcycle rider conspicuity captured by dark (red) upper body clothing is associated with significantly higher injury crash risk. Moreover, formal motorcycle driving training in recent years was associated with lower injury crash propensity. Finally, riders with less sleep prior to crash/interview had higher odds of crash involvement. Methodologically, the conclusion is that correlations of several riders, exposure, apparel, and riding history related factors with crash risk are not homogeneous (vary in magnitude and direction). The study results indicate the need to develop appropriate countermeasures, such as refresher motorcycle training courses and the prevention of riding when sleep-deprived/fatigued or under influence of alcohol/drugs.

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INTRODUCTION and BACKGROUND

Recent statistics reveal that the annual number of passenger car and light truck related fatalities have decreased by 32%, while those related to motorcycles have increased by 48% (NHTSA 2016). In order to enhance motorcycle safety, the United States Congress passed legislation initiating the most comprehensive research to investigate causes associated with motorcycle crashes (NHTSA 2017). Recent studies have focused on reducing the number of motorcycle crashes and unsafe outcomes (Chin and Quddus 2003, Goodwin *et al.* 2015). Numerous studies focused on investigating crash frequencies and injury severities of motorcycle related crashes. Different methodological approaches including ordered probit models (Quddus *et al.* 2002), multinomial logit (Shankar and Mannering 1996), mixed logit (Shaheed *et al.* 2013), and nested logit models (Savolainen and Mannering 2007) have identified factors related to motorcycle crash outcomes. Studies identified certain driver-related factors (Schneider *et al.* 2012), motorcycle characteristics (Savolainen and Mannering 2007), roadway geometrics (Quddus *et al.* 2002), and environmental factors (Rifaat *et al.* 2012) associated with injury severity. While such an analysis provides valuable insights into understanding the motorcyclists' injury outcomes, it does not shed light on the risk-taking behaviors of motorcyclists and how it relates to crash risk. Another area of continuing research is the motorcyclist's crash risk and its associated factors, and studies focused on investigating factors associated with motorcyclists' crash propensity. Motorcyclists are less risk averse than other motorized users (Broughton *et al.* 2009). Highly risky behaviors such as riding under the influence, speeding, inexperience, non-use of helmet, and unlicensed riding lead to higher crash rates (Schneider *et al.* 2012, Goodwin *et al.* 2015). Likewise, "frequent stunt" is related to higher crash odds (Stephens *et al.* 2017). While useful, such analyses usually do not reflect the exposure of the population under study (i.e., motorcyclists) to the outcome of interest (i.e., motorcyclist crash). Also, insights regarding the interrelationships between explanatory factors and actual crash propensity cannot be easily obtained.

This paper terms the chance of a rider getting involved in an injury crash as *"crash propensity".* In order to undertake actionable countermeasures, it is important to analyze differences in situational, rider-specific, and behavioral factors in a case-control (i.e., rider involvement in injury crash versus rider involvement in a non-crash event). Since the Hurt Study (1976-1980), no comprehensive research effort focusing on motorcycle crashes has been conducted in the U.S. (to the best of authors' knowledge). Outside the US, the Motorcycle Accidents in Depth Study (MAIDS) in Europe (ACEM 2000) and the On the Spot (OTS) study in the U.K. (Cuerden *et al.* 2008) sought to understand the causes of motorcycle crashes. This study investigates various psycho-physiological, exposure related, and behavioral factors associated with the probability of an injury crash in a match case control setup. A retrospective matched case-control design was adopted in the data collection to better understand the association of risk factors with motorcyclist crash propensity. The two units that constitute a case-control design are cases and controls. Cases in this context are riders involved in injury crashes during a specific time-period, whereas, controls are riders that are not involved in crashes during the same time period while exhibiting similar exposure as their case counterparts. The controls provide a basis for comparison of motorcycle, environment, and rider characteristics. To better understand crash propensity while accounting for overall exposure of the population (cases and controls in this study), each case is matched with two controls by time of day, day of week, weather, road type, urban/rural, location, and travel direction. Thus, matched case controls (riders not involved in a crash) are matched and combined with case events (riders involved in a crash) for analysis. Furthermore, this study addresses the observed and unobserved heterogeneities within and between matched case-controls. Unlike commonly used random parameters models, this study accounts for possible heterogeneity in the means of the random parameters which vary as a function of several observed factors. To the best of authors' knowledge, the use of such a method has not been used or reported in a retrospective matched case-control design context.

METHODOLOGY

Development of Case-Control Strategy

The notion of *crash propensity* refers to the likelihood of the motorcyclist's involvement in an injury crash event. *Risk factors* refer to the explanatory variables associated with an increased likelihood of motorcycle crash. Crash frequency data are typically analyzed to understand the risk factors associated with motorcycle crashes (Chin and Quddus 2003). While useful, such an analysis usually does not reflect the exposure of the population under study (i.e., motorcyclists) to the outcome of interest (i.e., motorcyclist crash). To circumvent this, a retrospective matched case-control design is adopted in this research to better understand the association of risk factors with the motorcyclist crash propensity (Figure 2.1). The two units that assemble a case-control design are the *cases* and *controls*. *Cases* indicate riders involved in an injury crash while *controls* indicate riders not involved in a crash with similar exposure during the same time. In this study, two *controls* are matched with each *case* based on location, locality type, roadway type, travel direction, weather, time of day, and day of week (Figure 2.1). The *cases* and *controls* then generate a binary dependent variable for analysis later on in this study.

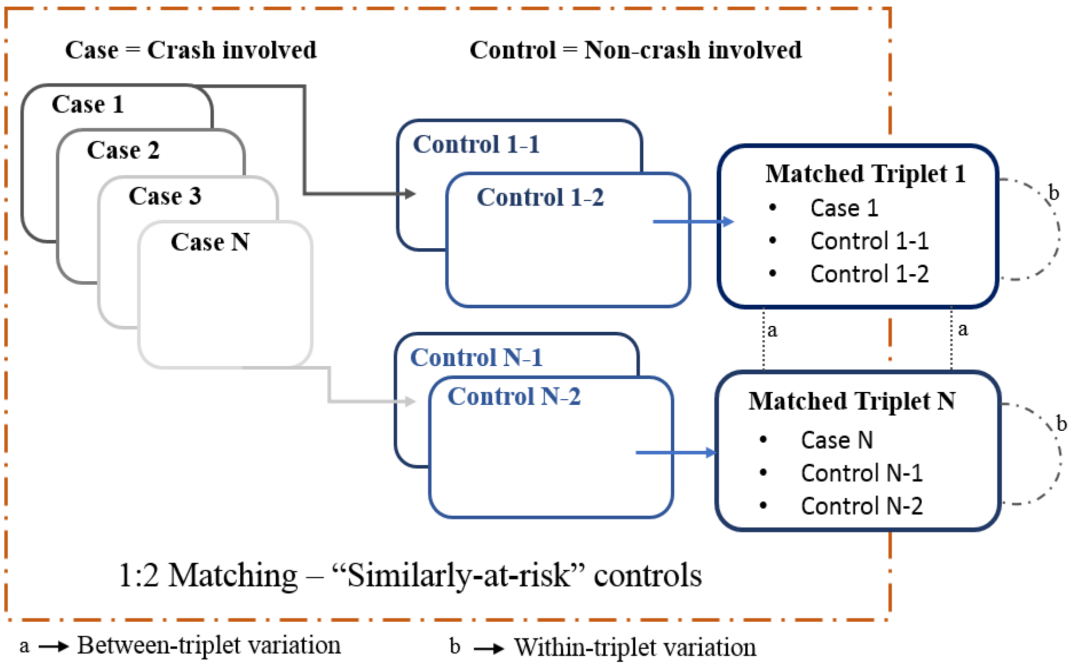

Figure 2.1: A Matched Case-Control Framework

Data

The methodological framework shown in Figure 2.1 is inspired by epidemiological and ecological research (Barzilai, Atzmon et al. 2003, Atzmon, Schechter et al. 2004). The proposed approach utilizes the methodological strengths in systematic analysis of case-control approaches by pairing presence and absence of injury crashes in this research (originally the presence/absence of a certain disease). The pairing of cases (e.g., presence of disease) and controls (absence of disease) leads to development of strata, which is a matched triplet in this research (Figure 2.1). The retrospective matched case-control approach shown in Figure 2.1 builds upon the Federal Highway Administration (FHWA) Motorcycle Crash Causation Study data (FHWA 2017). Importantly, MCCS is the most comprehensive data collection effort in the United States in more than 30 years legislated by the U.S. Congress and sponsored by the U.S. Department of Transportation (FHWA 2017). The dataset includes data from comprehensive on-scene investigations of 351 motorcycle injury crashes in Orange County, California and 702 control rider interviews (FHWA 2017). Given the focus of the present study, we mainly used Volume 2 (crash data form) and Volume 5 (motorcycle crash and control rider data) of the MCCS data for analysis. Data include detailed information of riders and crash sites during pre-crash, crash, and post-crash scenarios. Due to the well-known intrinsic limitations of police-reported crash data, injury, and other information provided in police-reported crash data can be subjective and bias (Wali, Khattak et al. 2018). To address these issues to the largest extent possible, the MCCS uses unique and rigorous protocols to collect injury data for crash involved riders. It is important to note that injury data reported in the MCCS is not solely obtained from police-reports, but, rather, comprehensive descriptions of all injuries (including minor) obtained by trained investigators through crash-involved motorcyclists' occupant interviews. Because access to medical information is carefully controlled through the United States 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 the MCCS study was conducted), the medical examiner also provided autopsy reports if applicable. Investigators then examined and encoded these exhaustive sets of records (Wali, Khattak et al. 2018).

Crash Propensity Models

Given the conceptual framework (Figure 2.1), the study carries out heterogeneity based statistical analysis while developing crash propensity models (i.e., fixed parameter and random parameter logit models). The details can be found in several papers including Tay 2016 (Fountas and Anastasopoulos 2017, Wali, Khattak et al. 2018); (Li, Khattak et al. 2017). The models were extended to matching structures in the data to capture the observed and unobserved heterogeneity related to between and within the matched triplets. For modeling details, please see Wali, Khattak et al. (2018).

RESULTS

Table 2.1 displays the descriptive statistics for important variables in both the controls and the (crash) cases. The outcomes of two-sample t-tests in both groups that help explain the significant difference in the means of important variables are provided. The "no difference" indicates that the null hypothesis cannot be rejected at a 95% confidence level (i.e., the two means are statistically not different), while "different" means that the null hypothesis can be rejected at 95% confidence level (i.e., the two means are statistically different). Relative to controls, the trips made by riders involved in injury crashes originated more frequently from workplaces or friend/relative places and less frequently from home. Also, riders with psychological or physical impairments seem to crash more frequently. Riders were observed in crash groups more frequently if they had four or more traffic convictions in the previous 5 years.

Almost every rider in the 1,053 observations was wearing a helmet (95% in the crash group). Furthermore "Full-Facial Coverage with Integral Chin Bar and Face Shield" was the most frequently observed category for crash passengers and for control passengers. Regarding motorcycle helmet coverage, compared to the control group, riders with helmet coverage type 1 (USDOT compliant helmets with partial coverage, least intrusive covering only the top half of the cranium) were less frequent in the injury crash group. Likewise, riders with acceptable helmet fit were also less frequent in the injury crash group. The finding that riders with partial helmet coverage are less frequent in crash group is intuitive; as full coverage helmets may interfere with the rider's hearing and vision capabilities, and thus may increase probability of crash. However, note that helmets are pivotal in reducing head injuries, given a crash (Brandt *et al.* 2002). Regarding overall helmet use, 100% of the control group riders were wearing helmets at the time of the interview. The helmet use among crash group riders was also high, i.e., riders in only 4 crashes were not wearing a helmet at the time of crash. Typically there are various styles of helmets which afford different protection: full-face, open-face, and half helmet (Figure 2.2). Riders with an acceptable helmet fit were less frequent in the crash group compared to control group.

a. Full-face b. Open-face c. Half helmet

Figure 2.2: Helmet Coverage Types

On average, riders in the crash group had fewer hours of sleep compared to the control group. Furthermore, the crash group had less experienced riders as reflected in riding experience and total miles driven prior to the event. Finally, riders in the control group had greater conspicuity (retroreflective upper body clothing) and wore more motorcycle-oriented clothing than the crash group.

Table 2.1: Descriptive Statistics of Key Variables

Variables	Crash Group (N = 351)		Non-Crash Group (N = 702)		Mean Comparison Test–H_o: $\mu_2 - \mu_1 = 0$
	(μ_1, SD)	(Min, Max)	(μ_2, SD)	(Min, Max)	
Trip Origin/Destination					
Origin: Home[a]	(0.30, 0.46)	(0, 1)	(0.89, 0.32)	(0, 1)	Different
Origin: Work[a]	(0.11, 0.31)	(0, 1)	(0.06, 0.25)	(0, 1)	Different
Origin: Friend/relative place[a]	(0.07, 0.26)	(0, 1)	(0.01, 0.12)	(0, 1)	Different
Destination: Friend/relative place[a]	(0.08, 0.27)	(0, 1)	(0.04, 0.20)	(0, 1)	Different
Frequency of road use					
First-time use[a]	(0.04, 0.20)	(0, 1)	(0.04, 0.19)	(0, 1)	No difference
Daily road use[a]	(0.33, 0.47)	(0, 1)	(0.37, 0.48)	(0, 1)	No difference
Road used once per week[a]	(0.10, 0.30)	(0, 1)	(0.34, 0.47)	(0, 1)	Different
Road used once per month[a]	(0.04, 0.20)	(0, 1)	(0.20, 0.40)	(0, 1)	Different
Road used once per quarter[a]	(0.01, 0.12)	(0, 1)	(0.03, 0.18)	(0, 1)	No difference
Type of helmet coverage*					
Helmet coverage type 1 (partial coverage)[a]	(0.12, 0.32)	(0, 1)	(0.32, 0.47)	(0, 1)	Different
Helmet coverage type 2 (full coverage)[a]	(0.03, 0.18)	(0, 1)	(0.04, 0.19)	(0, 1)	No difference
Helmet coverage type 3 (full facial, retractable chin bar)[a]	(0.04, 0.20)	(0, 1)	(0.05, 0.22)	(0, 1)	No difference
Helmet coverage type 4 (full facial, integral chin bar and face shield)[a]	(0.47, 0.50)	(0, 1)	(0.50, 0.50)	(0, 1)	No difference
Helmet fit**					
Helmet fit (1 if acceptable fit, 0 otherwise)[a]	(0.50, 0.50)	(0, 1)	(0.94, 0.24)	(0, 1)	Different
Physical/psychological factors					
No physical impairment[a]	(0.35, 0.48)	(0, 1)	(0.77, 0.42)	(0, 1)	Different
No psychological impairment[a]	(0.44, 0.50)	(0, 1)	(0.81, 0.39)	(0, 1)	Different
Hours of sleep prior to event	(7.67, 1.24)	(2, 12)	(8.12, 1.75)	(1, 16)	Different
Exposure-related factors					
Motorcycle riding experience in years	(11.52, 13.63)	(0, 46)	(20.48, 17.07)	(0, 69)	Different
Total miles driven prior to event	(10.35, 16.63)	(1, 96)	(19.05, 33.83)	(1, 600)	Different
Number of traffic convictions in last 5 years					
One traffic conviction	(0.16, 0.37)	(0, 1)	(0.23, 0.42)	(0, 1)	Different
Two traffic convictions	(0.11, 0.31)	(0, 1)	(0.10, 0.30)	(0, 1)	No difference
Three traffic convictions	(0.03, 0.18)	(0, 1)	(0.04, 0.19)	(0, 1)	No difference
Four or more traffic convictions	(0.52, 0.50)	(0, 1)	(0.04, 0.21)	(0, 1)	Different
Rider's apparel					
Retroreflective upper body clothing	(0.13, 0.34)	(0, 1)	(0.20, 0.40)	(0, 1)	Different
Clothing motorcycle oriented	(0.05, 0.21)	(0, 1)	(0.25, 0.44)	(0, 1)	Different
Actual speed before event	(32.84, 17.24)	(0, 90)	(46.35, 10.90)	(0, 85)	Different

Notes: *Sample size is indicated by N; μ_1 is the mean of the crash-group; μ_2 is the mean of the control-group; SD is standard deviation; Ho is the null hypothesis; (a) are indicator variables (1/0); "No difference" indicates that the null hypothesis cannot be rejected at 95% confidence level (the two means are statistically not different). "Different" indicates that the null hypothesis can be rejected at 95% confidence level (the two means are statistically different); For descriptive statistics of all variables please see* Wali, Khattak et al. (2018). **indicates that there are several other types of helmet coverage in the MCCS data which are not* *presented in the Table 2.1. for simplicity; they include: full-facial coverage, integral chin bar but no face shield; full-facial coverage, removable chin bar; open-face helmet with flat wraparound face shield; open-face helmet with bubble-type face shield; open-face helmet with visor/face-shield combo; open-face helmet with removable gravel guard; not applicable, no helmet; other (specify); and unknown. **indicates that there are several other categories in the MCCS data which are not presented in Table 2.1. for simplicity; they include: too large, too loose; too small, too tight; contour mismatch; not applicable, no helmet; other (specify); and unknown.*

Initially, the estimated fixed parameter logit models investigated key correlates of motorcycle crash propensity. Developed random parameter logit models captured unobserved heterogeneity. The AIC and likelihood ratio test statistics compare fixed parameter and random parameter logit models. Similarly, random parameter models with heterogeneity in means capture observed heterogeneity (as well as unobserved heterogeneity). As mentioned, this study estimated these models at individual observation levels as well as matched triplet levels. The random parameters and random intercepts with heterogeneity-in-means performed the best with the lowest AIC score (Table 2.2). After accounting for systematic & random heterogeneity, no significant "within" triplet dependence and variation is observed. As discussed earlier, there exists a matching structure in the data, where two controls are matched with each focal crash (case) by common matching characteristics. Thus, the empirical framework is extended to also account for both within and between triplet variation and heterogeneity (see methodology section for details). Apart from Model 1 (fixed parameter logit), the goodness-of-fit results of all competing models suggest that the heterogeneity models which operate at individual observation level clearly outperform their matched-triplet counterparts which provide compelling evidence that there is no significant triplet dependence and variation warranting estimation of heterogeneity models operating at matched-triplet level (Table 2.2).

Table 2.2: Comparison of Alternative Modeling Frameworks at Individual and Matched-Triplet Levels

Goodness of Fit Measures	Models for individual observations (ignoring matched-triplet structure)				Models for matched-triplets (accounting for matched-triplet structure)		
	Model 1*	Model 2**	Model 3***	**Model 4******	Model 5**	Model 6***	Model 7****
N (obs.)	1053	1053	1053	**1053**	1053	1053	1053
# of triplets	---	---	---	**---**	351	351	351
Degrees of Freedom	24	31	32	**39**	31	32	40
AIC	659.4	639.2	641.5	**633.2**	649.4	652.2	662.8

Notes: ** Fixed parameter model, ** Random parameters model, *** Random intercept and random parameters model, **** Random parameters/random intercepts with heterogeneity-in-means*

Given the goodness-of-fit statistics (Table 2.2) discussed above, the results of models operating at individual observation level are discussed in detail from here onwards. A total of 24 explanatory factors are included in the fixed parameter logit model (Model 1), out of which 17 variables were found to be statistically significant at the 95% confidence level. Regarding the random parameter logit model (Model 2), a total of seven explanatory factors were found to be normally distributed random parameters, suggesting that their associations with crash propensity vary significantly across crash events. These seven factors (i.e., normally distributed random parameters) include total miles driven prior to crash/interview, one traffic conviction, three traffic convictions, motorcycle-oriented clothing, female rider, rider is not the motorcycle owner, and speed greater than 50 miles per hour. As discussed, the goodness-of-fit statistics (i.e., Table 2.2) suggest that the logit model with heterogeneity-in-means random parameters across individual observations (Model 4) resulted in the best fit with the lowest AIC and Finite Sample AIC of 633.21 and 636.27 respectively, and highest McFadden Pseudo R^2 of 0.586. Five of the seven random parameters produced significant heterogeneity in the means as well (see Table 2.3). These five variables include total miles driven prior to crash/interview, one traffic conviction, three traffic convictions, female rider, and speed greater than 50 miles per hour (Table 2.3).

TABLE 2.3. Estimation Results for Fixed Parameter Logit, Random Parameter Logit, and Heterogeneity-in-Means Random Parameter Logit

Variables	Fixed Parameter Logit (Model 1)		Random Parameter Logit (Model 2)		Random Parameter Logit - Heterogeneity in Means (Model 4)	
	β	t-stat	β	t-stat	B	t-stat
Random Parameters						
Total miles driven prior to crash/interview	-0.003	-0.63	-0.026	-3.31	-0.008	-1.02
scale parameter	---	---	*0.064*	*6.5*	*0.051*	*5.49*
One traffic conviction	0.445	1.78	0.202	0.86	-0.309	-0.92
scale parameter	---	---	*1.596*	*5.31*	*1.65*	*5.24*
Three traffic convictions	0.484	1.01	-4.541	-2.29	-16.99	-2.54
scale parameter	---	---	*19.125*	*3.5*	*33.8*	*2.98*
Lower clothing motorcycle oriented	-1.497	-4.35	-4.519	-4.95	-6.5	-4.76
scale parameter	---	---	*4.988*	*5.45*	*7.24*	*5.41*
Female rider	0.41	0.93	-0.066	-0.15	0.39	0.73
scale parameter	---	---	*2.286*	*3.51*	*1.71*	*2.74*
Rider is not the owner	-0.741	-1.57	-0.872	-1.68	-1.16	-2.15
scale parameter	---	---	*2.439*	*3.39*	*2.89*	*3.75*
Speed greater than 50 mph	-1.415	-3.96	-2.687	-4.55	-2.98	-4.6
scale parameter	---	---	*3.417*	*4.93*	*3.49*	*4.77*
Heterogeneity in the Means of Random Parameter (Total miles driven prior to crash/interview)						
Origin: Work	---	---	---	---	*0.037*	*1.87*
Single rider	---	---	---	---	*-0.044*	*-3.38*
Heterogeneity in the Means of Random Parameter (Three traffic convictions)						
Origin: Work	---	---	---	---	*8.249*	*1.99*
Single rider	---	---	---	---	*13.08*	*2.74*
Training between 2001-2010	---	---	---	---	*-9.037*	*-2.18*
Heterogeneity in the Means of Random Parameter (One traffic conviction)						
Single rider	---	---	---	---	*0.852*	*1.99*
Heterogeneity in the Means of Random Parameter (Female rider)						
Hispanic or Latino rider	---	---	---	---	*-1.105*	*-1.56*
Heterogeneity in the Means of Random Parameter (Speed greater than 50 mph)						
Alcohol and multiple drugs	---	---	---	---	*2.628*	*2.57*

TABLE 2.3. Estimation Results for Fixed Parameter Logit, Random Parameter Logit, and Heterogeneity-in-Means Random Parameter Logit *(Continued)*

Variables	Fixed Parameter Logit (Model 1)		Random Parameter Logit (Model 2)		Random Parameter Logit - Heterogeneity in Means (Model 4)	
	β	t-stat	β	t-stat	β	t-stat
Fixed Parameters						
Constant	3.32	4.8	4.41	6.21	4.62	6.1
Origin: Home	-2.46	-7.97	-3.00	-8.04	-3.08	-7.86
Origin: Work	-1.24	-3.12	-1.68	-4.05	-2.09	-4.25
Destination: Friend/relative place	1.36	3.66	1.49	4.06	1.55	4.32
5 hours or less sleep	0.92	2.43	1.07	3.31	1.09	3.36
Road used daily	0.46	2.02	0.46	2.09	0.5	2.26
Road used once per month	-0.85	-2.27	-1.08	-2.8	-1.06	-2.6
Helmet coverage type 1 (Partial coverage)	-0.76	-2.71	-0.73	-2.63	-0.68	-2.45
Training between 2001-2010	-1.05	-3.78	-1.21	-4.44	-1.15	-4.13
Training between 2011- 2015	-1.33	-4.14	-1.48	-4.88	-1.43	-4.68
Two traffic convictions	0.828	2.77	0.82	2.76	0.85	2.87
Upper body clothing color: Red	1.131	2.47	1.27	2.8	1.38	3.04
Motorcycle license being held by the rider for 30 or more years	-0.481	-1.38	-0.44	-1.27	-0.36	-1.01
Hispanic or Latino driver	0.544	2.06	0.70	2.67	0.77	2.71
Rider age in years	-0.029	-3.09	-0.03	-3.44	-0.04	-3.79
Rider weight in pounds	-0.004	-1.8	-0.01	-2.66	-0.007	-2.62
Rider is college/university graduate	-0.295	-1.15	-0.29	-1.14	-0.28	-1.06

DISCUSSION

The estimation results (Table 2.3) indicate that there are several factors associated with motorcycle crash propensity, consistent with the descriptive statistics. Table 2.4. shows relative risks of certain variables show the percent changes in the odds of a rider getting involved in an injury crash. In the discussion of results, the word “crash” is used to refer to an injury crash. We briefly discuss the key estimation results in this section. Please note that the discussion is mainly based on the estimation results obtained from Model 4, given its best fit among all the competing models (Table 2.2).

Riders who wore motorcycle-oriented clothing (e.g., leather pants or tighter jeans), showed lower injury crash risk. Despite some heterogeneity in this association, a substantial portion of the sample, i.e., 81.5%, is observed to have a positive correlation between motorcycle-oriented clothing and lower crash risk. This relationship may also reflect to some extent that the rider is relatively safety oriented. Likewise, wearing conspicuous (upper body) clothing was associated with lower risk of getting involved in injury crashes. Overall, apparel and conspicuity can make a difference in crash and injury risks, indicating that motorcycle safety can be potentially improved through greater awareness of motorcyclists adopting these strategies to reduce the risk levels.

Table 2.4. Relative Risk Estimates for Motorcycle Crash Propensity

Variables	Fixed Parameter Logit (Model 1)		Random Parameter Logit (Model 2)		Random Parameter Logit - Heterogeneity in Means (Model 4)	
	Direction of association	% change in crash risk	Direction of association	% change in crash risk	Direction of association	% change in crash risk
Exposure-related factors						
Total miles driven prior to event	↓	-0.300	[↓]	-2.57	[↓][a]	-0.80
Number of traffic convictions in last 5 years						
One traffic conviction	↑	56.05	[↑]	22.38	[↓][a]	-26.58
Two traffic convictions	↑	128.87	↑	127.28	↑	133.96
Three traffic convictions	↑	62.26	[↓]	-98.93	[↓][a]	-101.00
Clothing						
Lower clothing motorcycle oriented	↓	-77.62	[↓]	-98.91	[↓]	-99.85
Upper body clothing color: Red	↑	209.88	↑	254.31	↑	297.49
Rider-related factors						
Motorcycle license being held by the rider for 30 or more years	↓	-38.18	↓	-35.85	↓	-30.23
5 hours or less sleep	↑	150.93	↑	191.54	↑	197.43
Female rider	↑	50.68	[↓]	-6.39	[↑][a]	47.70
Rider is not the owner	↓	-52.34	[↓]	-58.19	[↓]	-68.65
Hispanic or Latino rider	↑	72.29	↑	101.78	↑	115.98
Rider age in years	↓	-2.86	↓	-2.96	↓	-3.92
Rider weight in pounds	↓	-0.399	↓	-0.60	↓	-0.70
Rider is college/university graduate	↓	-25.55	↓	-25.32	↓	-24.42
Trip-related factors						
Origin: Home	↓	-91.46	↓	-95.04	↓	-95.40
Origin: Work	↓	-71.06	↓	-81.40	↓	-87.63
Destination: Friend/relative place	↑	289.62	↑	341.94	↑	371.15
Frequency of road use						
Road used daily	↑	58.41	↑	57.93	↑	64.87
Road used once per month	↓	-57.26	↓	-66.14	↓	-65.35
Type of helmet coverage						
Helmet coverage type 1 (Partial coverage)	↓	-53.23	↓	-51.81	↓	-49.34
Year of training						
Training between 2001-2010	↓	-65.01	↓	-70.09	↓	-68.34
Training between 2011- 2015	↓	-73.55	↓	-77.26	↓	-76.07
Speed before crash/interview						
Speed greater than 50 mph	↓	-75.71	[↓]	-93.19	[↓][a]	-94.92

Notes: *Brackets indicate mixed effects for the random-held parameters, (a) indicates random parameters with heterogeneity-in-means*

It should be noted that motorcycle rider conspicuity, i.e., detectability and visibility on road, is regarded as a “high-priority” key risk factor in the recent USDOT’s National Agenda for Motorcycle Safety (NHTSA 2013). One of the key finding of 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, Ouellet et al. 1981). We found that the odds of riders wearing non-conspicuous (upper body) clothing getting involved in a crash were 297% higher which might be because dark color clothing reduces conspicuity (Wells *et al.* 2004). This is intuitive as dark color upper clothing may reduce the motorcycle rider’s conspicuity. Also, past research by (Wells, Mullin et al. 2004) found that dark colored helmets and dark waist up clothing (lower conspicuity) are typically associated with a higher likelihood of injury involved crashes (Wells, Mullin et al. 2004). Notably, there are substantial variations in the relative risks surrounding proper clothing and conspicuity.

As mentioned before, almost everyone in the sample was wearing a helmet. Therefore, this study does not assess whether wearing a helmet is associated with injuries. Instead, this analysis focuses on the type of helmet worn. As indicated by the descriptive of the data, crash cases had substantially less use of type 1 (partial coverage) helmets than the control group. The modeling results confirm this finding, i.e., helmets with type 1 coverage are associated with 49% lower odds of crash involvement than other types of helmets. Partial coverage helmets may not interfere with the rider’s hearing and vision capabilities and are associated with lower odds of crashes.

If a rider received training in recent years, the odds of crash involvement is lower by 69% and 77% for training between 2001–2010, and 2011–2015, respectively. This finding is also intuitive as motorcycle rider training programs in recent years have significantly improved due to the national and statewide efforts for improving motorcycle safety (NHTSA 2013). All the above findings relate to “policy-sensitive” and “preventable” key risk factors. For instance, encouraging riders to increase their conspicuity using motorcycle-oriented rider clothing may reduce motorcycle crashes. Likewise, awareness programs aimed at encouraging motorcycle riders to participate in formal training programs can also alleviate the crash risks stressing the importance of refresher courses. Several other rider behavioral, demographic, traffic related conviction history, exposure-related, and trip related factors have significant associations with rider crash propensity, detailed discussion available in the paper (Wali *et al.* 2018b).

LIMITATIONS

The present study is based on a sample of 1053 events in Orange County, California out of which 351 were identified as injury crash events. This study uses MCCS data which is the most comprehensive national effort to-date. However, the results should be interpreted with caution due to the limited sample size. Also, the data are collected in Orange County, California and may not be representative of motorcyclists in other areas of California and the United States. The matched case-control design allows efficient analysis of rare diseases (injury crashes) while controlling for the exposure of population under study (i.e., motorcyclists) to the outcome of interest (i.e., motorcyclist crash). However, a frequently reported disadvantage of matched case-control studies is the retrospective nature. That is, the study framework looks backwards and investigates exposure to crash risk. As such, retrospective studies may be exposed to errors related to confounding and bias. However, as the investigations in this study are performed in field by trained experts, and do not build on investigator’s memory per se, the extent of confounding and recall bias is likely small.

CONCLUSIONS

This study investigates various “policy-sensitive” factors related to a motorcyclist’s crash risk while controlling for certain rider-specific, physical and psychological, and other factors (observed/unobserved). Analysis used matched case-control data from the Motorcycle Crash Causation Study (MCCS) which included 351 cases (riders involved in crashes) and 702 matched controls (riders not involved in crashes). A heterogeneity-based case control approach computed the relative risks of various “policy sensitive” factors while considering possible observed and unobserved heterogeneity. This study estimated various logit frameworks including a fixed parameter logit model, random parameter logit models, and heterogeneity-in-means random parameter logit models both at the individual observation level as well as at the matched triplet level. At the observation level, heterogeneity-based models showed better performance than their respective matched-triplet levels. Random parameter logit models (with heterogeneity-in-means) had the best fit among competing models for capturing observed and unobserved heterogeneity. Given the estimation results, partial helmet coverage (half face motor vehicle, motorcycle helmets) is associated with a lower probability of a crash. Dark upper body clothing are associated with increase in injury crash risk. Also, the chance of rider involvement in an injury crash was lower if riders wear motorcycle-oriented clothing. All of these findings relate to “policy-sensitive” and “preventable” key risk factors. The conclusions are that reductions in motorcycle injury crashes are possible by encouraging helmet usage, increasing rider conspicuity and/or using motorcycle oriented lower clothing. The results of this study indicate that motorcyclist safety could be improved through ongoing participation in motorcycle training programs (perhaps through refresher courses for experienced motorcyclists), prevention of sleep-deprived/fatigued riding, and riding under the influence of alcohol and/or drugs (especially at high speeds). This study provides a base for simulation modeling which can help local and state agencies prioritize road safety programs to enhance motorcycle safety.

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3. Modeling Injury Severity Score as a More Precise Measure of Motorcyclist Injuries: A Correlated Random Parameter Corner Solution Framework

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Access the paper at: https://www.sciencedirect.com/science/article/abs/pii/S0001457518304883

Abstract
Motorcyclists are vulnerable road users at a particularly high risk of serious injury or death from crashes. In order to evaluate key risk factors in motorcycle crashes, this study quantifies how different "policy-sensitive" factors (e.g., year of motorcycle training, conspicuity and/or using motorcycle oriented rider clothing) 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 in FHWA's comprehensive Motorcycle Crash Causation Study (MCCS) using an anatomical injury severity scoring system termed as the Injury Severity Score (ISS). The ISS is a medical scoring system based on AIS that accounts for the possibility of multiple injuries to different body parts by considering the three out of six most severely injured ISS body regions according to their calculated AIS scores ($ISS = X^2 + Y^2 + Z^2$). Compared to the commonly used KABCO or AIS systems, ISS is an established medical scoring system used for assessing trauma severity, and correlates with mortality, morbidity and hospitalization time after trauma. In addition, the Abbreviated Injury Scale (AIS) tends to underestimate injury severity. For modeling, fixed and random parameter Tobit modeling frameworks in corner-solution settings account for the left-tail spike in the distribution of ISS and for unobserved heterogeneity. Additionally, the developed random parameters Tobit framework accounts for the interactive effects of key risk factors, given a crash, which reveals possible correlations among random parameters. A correlated random parameter Tobit model was found to significantly out-perform uncorrelated random parameter Tobit and fixed parameter Tobit models. Several findings related to rider experience, helmet coverage, and alcohol/multiple drugs intake are quantified.

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INTRODUCTION and BACKGROUND
Motorcyclists are more vulnerable to injuries and fatalities in crashes than vehicle occupants. Some studies have investigated how certain roadway environments, traffic related factors, and roadway geometric factors influence motorcycle crash risk (Haque, Chin et al. 2012) (Chin and Quddus 2003). Such studies have identified key factors associated with crash risk, but they do not provide insights about how these factors influence various injury outcomes. Several other studies have investigated factors associated with injury severity in motorcycle crashes (Savolainen and Mannering 2007, Chung, Song et al. 2014). These studies utilized various discrete outcome approaches like ordered probit, multinomial logit, mixed logit, and nested logit models to model injury severity from motorcycle crashes (Mannering and Bhat 2014). They found that several factors related to rider, roadway geometry, environment, and motorcycle attributes are associated with crash severity (Schneider, Savolainen et al. 2012). One of the key studies provides effective countermeasures for enhancing motorcycle safety (Goodwin, Thomas et al. 2015). However, due to the

unavailability of more detailed data on motorcycle crashes, several gaps exist. For instance, most of the motorcycle crash severity studies analyzed police reported crash data (Quddus, Noland et al. 2002) which can be subjective and biased (Mannering and Bhat 2014). Such reports provide information about the most severe injuries sustained by the riders and do not provide details about potential injuries to other body parts. Also, police reports do not provide information on other important factors such as pre-crash speed, physical conditions, and other important pre-crash rider' behaviors. In addition, police crash reports usually do not contain information about the motorcyclist's experience, conspicuity, socio-demographics, helmet type and coverage (Shaheed, Gkritza et al. 2013). These factors are high-priority risk factors in the current USDOT's National Agenda for Motorcycle Safety. Given the predominant gaps related to motorcycle injury severity literature, this study analyzes the enriched MCCS data source to investigate the effects of rider-related factors (rider age, physical impairment, and alcohol and drug intake) on various injury outcomes (given a crash) while accounting for correlated and uncorrelated unobserved factors in a corner solution setup.

METHODOLOGY

Data Source and Injury Classification

This study analyzes 321 out of the 351 crashes, because for these cases the MCCS data reported injury severity. The data provide detailed information regarding the rider's pre-crash, crash, and post-crash attributes and the crash locations. The data also include extensive information about traffic, roadway, and environment factors that could be associated with motorcycle crash occurrence and severity (FHWA 2017). Different injury classification scales are used to classify injuries sustained by drivers/riders, given a crash. One injury classification system, Abbreviated Injury Scale (AIS) has 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 injury scale; 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 the KABCO/AIS scale 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. Fortunately, the MCCS provides injury severity information (in AIS scale) 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 Stevenson, Segui-Gomez et al. 2001. The availability of detailed injury data for each of the body part allows quantification of injury severity through Injury Severity Score (ISS) that accounts for riders with multiple injuries (Stevenson, Segui-Gomez et al. 2001). 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 (Stevenson, Segui-Gomez et al. 2001). The ISS is based upon the Abbreviated Injury Scale (AIS) (see below). To calculate the ISS, 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 (Stevenson, Segui-Gomez et al. 2001). 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 during 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, Segui-Gomez et al. 2001). The ISS scores range from 1 to 75. If any of the three AIS scores is 6 (meaning un-survivable 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.

Modeling

This paper models ISS, which indicates the injury severity of a rider on a scale of 1 to 75, 1 being the lowest level of injury severity sustained by a rider. The distribution in our case contains a left spike at 1, i.e., a corner solution (Figure 3.1). While clearly acknowledging that this is not a censoring issue per se (explained in the paper), censored regression models can solve corner-solution problems (Wooldridge, 2010). 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, a survey sample may include people of all income levels, but 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, a corner solution (as is the case in this study and in almost every safety outcome application) is not a data observability issue or defect in the sample. In the case of a 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 a continuous random variable over strictly positive value. 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. In this study, the distribution contains a left spike, which is a corner solution and not censored data. However, a censored regression can account for a corner-solution setup (Wooldridge 2010) (Greene 2003). Therefore, this study develops a tobit regression model (Anastasopoulos, Mannering et al. 2012). To account for unobserved heterogeneity, the model includes random parameter in the standard tobit setup (Greene 2003) (Fountas, Sarwar et al. 2018). Different models are compared through goodness-of-fit measures such as the likelihood ratio test and AIC (Wali, Khattak et al. 2018).

RESULTS

Descriptive Statistics

The ISS values for this sample vary from 1 to 75 and average at 10.32. A value of 9 or more is considered a serious injury (Stevenson, Segui-Gomez et al. 2001). The results exhibit a spike at 1 (very minor injury) in the left corner, indicating a corner solution setup (Figure 3.1). A comparison between the ISS and AIS values of the sample reveals how AIS can underestimate the true injury severity sustained by a rider (Table 3.1). While there is a high correlation between the two measures as expected, an important insight from this cross-tabulation relates to how AIS and ISS classify "maximum (untreatable)" injuries. Specifically, 100 percent of the injuries classified as "maximum (untreatable)" injuries by AIS are classified likewise by ISS. However, 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 in AIS. The AIS measure was compared with ISS and ISS was found to be better based on theory and empirical evidence.

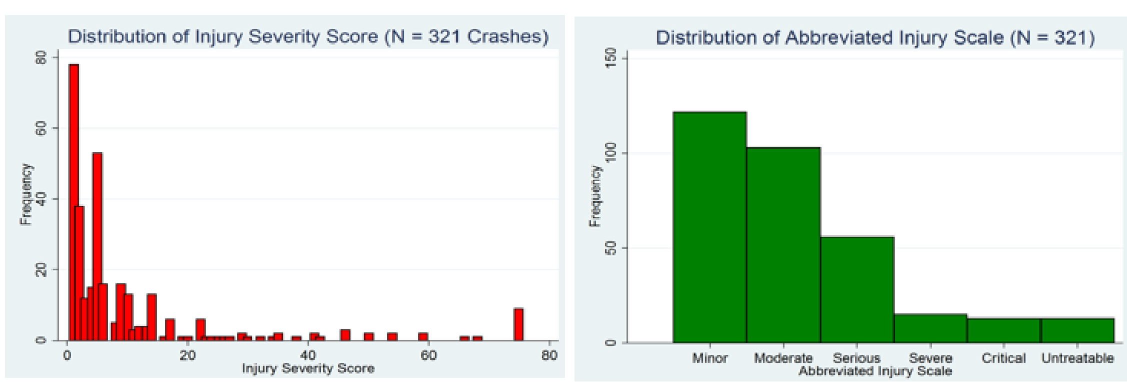

Figure 3.1: Distribution of Injury Severity Scores and Abbreviated Injury Scale for the Sampled Crashes

Table 3.1: Tabulation of Abbreviated Injury Scale and Injury Severity Score

AIS Categories	ISS 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						

Table 3.2. presents the summary statistics for the response and key explanatory variables. Only 4.6% crashes involved riders who had previously attended a training/experience course. In addition, 7.4% of riders had a positive reported Blood Alcohol Concentration (BAC) and 5.6% had reportedly taken multiple drugs or depressants.

Table 3.2: Descriptive Statistics of Key Variables

Variables (N = 321)	Mean	SD	Min	Max
Dependent Variable: Rider Injury Severity Score (ISS)	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 (i.e., intermittent riding) (1/0)	0.198	0.399	0	1
Rider course (1/0)	0.046	0.211	0	1
Rider Apparel & Conspicuity Related Factors				
Upper body clothing retroreflective (1/0)	0.139	0.347	0	1
Upper clothing motorcycle oriented (1/0)	0.337	0.474	0	1
Shoes motorcycle oriented (1/0)	0.167	0.374	0	1
Dark blue color waist down clothing (1/0)	0.372	0.484	0	1
Helmet color (multicolor)	0.074	0.263	0	1
Helmet color (White)	0.062	0.241	0	1
Helmet color (silver, grey)	0.056	0.230	0	1
Helmet color (Black)	0.427	0.495	0	1
Helmet Related Factors				
Half face motor vehicle, motorcycle helmet (1/0)	0.105	0.307	0	1
Acceptable helmet fit (1/0)	0.545	0.499	0	1
Alcohol/Drugs Intake				
Positive Blood Alcohol Concentration (1/0)	0.074	0.263	0	1
Rider took depressant or multiple drugs (1/0)	0.056	0.230	0	1
Rider Specific Factors				
Height of rider	5.857	0.278	4.916 7	6.75
Age of rider at time of crash (years)	36.022	14.175	16	73
Rider has no physical impairment (1/0)	0.372	0.484	0	1
Ethnicity: Black rider (1/0)	0.046	0.211	0	1
Crash Specific Factors				
Travel speed before crash (mph)	36.288	16.209	0	96
Time indicator: Time in seconds from precipitating event to impact (1 if > 2.3, 0 otherwise)	0.498	0.501	0	1
Distance indicator: Distance in feet between POI to POR (1 if > 9, 0 otherwise)	0.492	0.501	0	1
Two-way undivided highway (1/0)	0.316	0.466	0	1
Level grade (1/0)	0.554	0.498	0	1
Motorcycle running off roadway, no other vehicle involvement (1/0)	0.077	0.268	0	1
Negotiating a curve, constant speed (1/0)	0.127	0.333	0	1

***Notes:** Sample size = 321 injury crashes. For indicator variables, 1 indicates "Yes" and 0 "otherwise". Experienced rider course means participation in training between 2001–2010, and training between 2011–2015). While "gaps" indicate that rider were not frequent or routine riders.*

Modeling Results

This study estimates a fixed parameter Tobit, uncorrelated random parameter Tobit (URPT), and correlated random parameter Tobit (CRPT) models. In fixed parameter approaches, parameters remain fixed throughout observations but can vary across observations in uncorrelated models to capture unobserved heterogeneity. 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 is applied for the covariance matrix of random parameters (Wali, Khattak et al. 2019) which does not allow for potential correlations among the explanatory factors treated as random parameters. The random parameters tracking the possible unobserved heterogeneity are assumed to be uncorrelated which is rather a very restrictive assumption. Failure to account for correlation effects among randomly distributed effects of explanatory factors can result in several misspecification issues, such as biases, inconsistent parameter estimates, and/or erroneous inferences. Given that random parameters can be correlated, the CRPT approach overcomes the inconsistent, biased, and erroneous estimates related to the uncorrelated model. To address this important methodological concern, correlated random parameter Tobit models 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, thus termed as CRPT. The variance–covariance matrix for the random parameters' distribution is set to follow a multivariate normal distribution. The results of correlated random parameter Tobit model (CRPT) are shown in Table 3.3, whereas the lower panel of Table 3.4 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 3.4). As can be seen in Table 3.3, 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. Overall, as shown in Table 3.3, a total of six correlated random parameters are found in this study: 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 ISS vary statistically significantly across the sampled observations due to systematic variations in unobserved factors. The interpretation of (correlated) random parameters is presented in the subsequent discussion. The lower Akaike Information Criterion (AIC) of the uncorrelated random parameter model indicates its supremacy over the fixed parameter Tobit approach while capturing unobserved factors. The AIC of CRPT is considerably lower than the URPT model, which suggests correlations among the unobserved factors (Table 3.3).

Finally, to better interpret the results of the Tobit models, Table 3.5 also presents the marginal effects of the selected explanatory factors on the expected value of y (censored and uncensored) for the best-fit correlated random parameter Tobit model. To highlight differences in magnitudes of effects, the marginal effects for fixed parameter Tobit and uncorrelated random parameter Tobit are also shown in Table 3.5. Interesting findings regarding the correlations between the rider ISS and key explanatory variables pertaining to the study objectives are discussed next.

Table 3.3: Estimation Results for Fixed Parameter Tobit, Uncorrelated Random Parameter Tobit, and Correlated Random Parameter Tobit 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)	6.27	1.83	3.42	2.36	0.41	5.81	3.07	0.28	10.8
Standard deviation*	-	-	-	13.38	0.30	44.36	15.04	0.28	53.75
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	10.85
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			-934.1758			-914.9497		
AIC	2004.3			1936.4			1925.9		

Notes: *β is the 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; AIC is Akaike Information Criteria: BAC is blood alcohol concentration; LL(β) is log-likelihood at convergence.*

Table 3.4: Variance Covariance (Cholesky Matrices) for Uncorrelated Random Parameter Tobit, and Correlated Random Parameter Tobit Models

Correlated Random Parameter Tobit (URPT) Cholesky Matrix						
	Distance in feet between POI to POR (1 if > 9, 0 otherwise)	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)	15.03 [50.43] (1.00)					
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)				
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)			
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)		
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)	
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*

Table 3.5: Selected Marginal Effects of Fixed Parameter Tobit, Uncorrelated Random Parameter Tobit, and Best-Fit Correlated Random Parameter Tobit Models

	Fixed Parameter Tobit		Uncorrelated Random Parameter Tobit		Correlated Random Parameter Tobit	
Variables	**ME-1**	**ME-2**	**ME-1**	**ME-2**	**ME-1**	**ME-2**
Rider Apparel & Conspicuity Related Factors						
Upper body clothing retroreflective (1/0)	-2.58	-1.81	-2.04	-1.98	-1.89	-1.89
Shoes MC oriented (1/0)	-3.42	-2.40	-5.58	-5.42	-5.95	-5.94
Upper clothing MC oriented (1/0)	4.03	2.83	4.40	4.27	3.21	3.21
Blue color waist down clothing (1/0)	1.33	0.93	5.30	5.14	5.45	5.44
Helmet color (silver, grey)	-3.74	-2.62	-7.74	-7.51	-7.56	-7.55
Helmet color (Black)	4.87	3.42	5.44	5.28	4.25	4.25
Rider Experience Related Factors						
Gap exists between riding (1/0)	1.52	1.07	4.12	4.00	3.39	3.39
Experienced rider course (1/0)	-7.00	-4.92	-7.69	-7.46	-8.21	-8.20
Helmet Related Factors						
Half face motor vehicle, motorcycle helmet (1/0)	4.10	2.88	4.87	4.72	5.31	5.31
Acceptable helmet fit (1/0)	-5.93	-4.17	-9.56	-9.27	-8.82	-8.81
LL(β)	-975.154		-935.175		-914.945	
AIC	2004.3		1936.4		1925.9	

Notes: *(*) MC is motorcycle; ME-1, ME-2 show the effect of a unit change in explanatory factor on the expected value of censored and uncensored ISS and on the expected value of uncensored ISS outcomes respectively*

DISCUSSION

The estimation outcomes reveal several interesting insights. Given a crash, partial helmet coverage is positively correlated with higher ISS. This finding is consistent with past literature (Rivara et al. 1999). Such helmets are USDOT compliant 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 pose a higher risk of injury, given a crash. It was found that such helmets are also associated with lower crash risk in the previous chapter--therefore the variable has opposing correlations with crash risk and injury risk given a crash. Notably, this variable has a normally distributed random parameter suggesting that the effects of this variable can vary significantly across observations. For instance, with a mean of 5.31 and standard deviation of 7.45 (refer to CRPT model in Table 3.3), the associations between partial coverage helmets and the injury severity score are positive for 76.2% of the observations and negative for the rest.

A rider with an acceptable helmet fit had significantly lower injury severity score by 8.81 units, given a crash (Table 3.5). These findings agree 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 heterogeneous in magnitudes with negative associations for 94.3% of the observations and positive associations for the rest (Table 3.3). 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) (Wali et al. 2019).

Riders with gaps between ridings (i.e., riding motorcycles intermittently) are more likely to have higher ISS scores. According to the correlated random parameter Tobit (CRPT) model results, riders who took a relevant course (training between 2001–2010, and training between 2011–2015) showed reductions of 8.20 units in ISS, compared to a 6.95-unit decrease indicated by the fixed parameter Tobit model (Table 3.3). This finding is intuitive as more experienced riders can better respond and handle the motorcycle in unsafe situations. Also, the best CRPT model outcomes show that ISS increases by 15.61 for positive BAC reported riders compared to an increase of only 7.09 and 2.75 units indicated by fixed parameter and uncorrelated random parameter Tobit models (Table 3.3). This finding is very important as it indicates the severe consequences of riding under the influence of alcohol. The BAC variable is also a normally distributed random parameter. Additionally, the ISS increases significantly when riders take anti-depressants/multiple drugs.

Regarding rider apparel type and conspicuity, we found that if a rider's shoes were motorcycle-specific, the injury severity score was lower significantly by 5.94 units (Table 3.3). 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 (de Rome 2006). In addition, motorcycle rider conspicuity, i.e., detectability and visibility on road, is regarded as a "high-priority" key risk factor in the USDOT'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, Ouellet et al. 1981). To this effect, our analysis shows that if the rider's upper body clothing was retroreflective, the injury severity scores was significantly lower.

Helmet color is also one of the factors that can increase or decrease rider conspicuity (Wells, Mullin et al. 2004, Gershon, Ben-Asher 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, Mullin 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 3.3), whereas light colored helmets (such as silver or grey) are associated with a significant decrease in the injury severity score (a decrease of 7.55 units). These findings agree with those of Wells et al. (2004) and are intuitive as usually dark colored helmets (such as black) can decrease rider conspicuity (especially at night), thus increasing the risk of injury (Wells, Mullin et al. 2004). Interestingly, our analysis shows that white colored helmets are also associated with a significant increase in the injury severity score, given a crash (see Table 3.3). 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, a white outfit can decrease rider's conspicuity where a background is solely a bright sky (such as on inter-urban roads) (Gershon, Ben-Asher et al. 2012).

Regarding rider experience related factors, if a rider had gaps between their riding (intermittent riding), they are more likely to sustain severe injuries. Contrarily, if a rider had taken a relevant course, then their injury severity score was lower on-average. Clearly, reductions in injury severity are possible by increasing rider conspicuity and/or by using motorcycle-specific clothing. The mentioned outcomes relate to risk factors (given a crash) that can be lowered. For example, training programs for riders can help reduce the severity of motorcycle crash outcomes. Also, the CRPT model, a key methodological contribution of this study, investigates the combined interactional effects of important factors on injury severity scores. The CRPT approach is more suitable than the UCRP approach as indicated by its lower AIC (Table 3.3).

Table 3.5 shows a selected set of results of correlations between key variables and ISS. In a censored regression framework, different marginal effects are of interest in terms of the effect of one-unit change in a predictor on either the censored/uncensored observations (ME-1 in Table 3.5) or only uncensored observations (ME-2 in Table 3.5). In context of fixed parameter censored modeling, these marginal effects are important and often different in magnitudes. Likewise, we have the effects from uncorrelated and correlated models. However, what we see methodologically is that the differences between different types of marginal effects significantly reduces or even disappear. Thus, different types of marginal effects that are relevant in the censored-regression framework may not be as relevant in the heterogeneity-based Tobit modeling. The results show that retro-reflectivity, proper apparel, experience, helmet fit, and helmet coverage all are associated with lower injury severity outcome, given a crash. Based on the goodness-of-fit statistics, correlated RP Tobit resulted in best-fit underscoring the importance of correlated unobserved heterogeneity. In addition, standard deviations and the statistical significance of the correlated random parameters are calculated using simulation-based draws relative to the corresponding Cholesky matrix (Table 3.4).

LIMITATIONS

The findings are based on MCCS sample of 321 injury crashes and may not represent the national population. Given the retrospective nature of MCCS, prediction of future risks based on the models presented may not be accurate. However, because trained experts performed the field investigations, concerns about the quality of data are limited.

CONCLUSIONS

This study examines various key risk factors associated with the injury severity of motorcycle crashes, such as riders' helmet type and coverage, experience, and alcohol and multiple drug usage. From a methodological standpoint, a developed corner solution framework addressing both uncorrelated and correlated unobserved heterogeneity. The study analyzes extensive data from the MCCS (FHWA) for 321 injury crashes involving motorcycles. The Injury Severity Score (ISS), which accounts for multiple injuries sustained by different body parts of the riders, is the response variable. Compared to ISS, AIS tends to underestimate the injury severity sustained by the rider. ISS provides a more accurate approximation to mortality prediction.

Because of this case's left-spike data distribution, the study developed a corner solution framework by estimating fixed parameter, uncorrelated random parameter, and correlated random parameter Tobit models. The results of the correlated random parameters model have the best fit. The correlated random parameter Tobi approach also reveals the interaction effects of unobserved factors on the ISS. This paper estimates the statistical significance of the standard deviation for correlated random parameters. Several key factors related to rider experience, alcohol/multiple drug use, apparel and head coverage had correlations with ISS. Several important findings surfaced from the empirical analysis. Regarding rider apparel type and conspicuity, we found that if a rider's shoes were motorcycle-specific, injury severity scores were lower. Given a crash, partial helmet coverage was positively correlated with higher ISS, which is intuitive as such helmets provide less coverage compared to full face helmets and thus pose a higher risk of injury. It was also found that such helmets are associated with lower crash risk. Therefore, the variable has opposing correlations with crash risk and injury severity risk given a crash. Further research is needed to explore in greater depth the opposing impacts found in this study and their implications. One implication can be to design helmets that have broader coverage, but also allow the rider to hear and see well. A rider with an acceptable helmet fit had significantly lower injury severity score, implying that strategies to improve the fit of helmets can potentially reduce injury severity. Finally, this study revealed that there are significant implications for ignoring correlated unobserved heterogeneity.

This study does not suggest any government policies, but the findings can help policy makers develop appropriate countermeasures and formulate policy. In the future, researchers can simultaneously model the injury severity sustained by different body parts of the same rider to account or unobserved heterogeneity. Also, one may examine the occurrence and outcomes of motorcycle crashes once connected and automated vehicle technology diffuses through the system.

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