TEMPORAL STABILITY ANALYSIS IN ROADWAY CRASH INJURY SEVERITIES RESEARCH WITH UNOBSERVED HETEROGENEITY

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การวิเคราะห์ความมั่นคงชั่วขณะ ในการวิจัยความรุนแรงของการบาดเจ็บจากอุบัติเหตุทางถนน ร่วมกับความแตกต่างที่ไม่สามารถสังเกตได้

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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรดุษฎีบัณฑิต
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การพัฒนาแบบจำลองความรุนแรงของอุบัติเหตุโดยใช้ชุดข้อมูลอุบัติเหตุ จำเป็นต้องพิจารณาสองประเด็น คือ การแปรเปลี่ยนแบบชั่วคราวของปัจจัย และปัจจัยใจความแตกต่างที่ไม่สามารถสังเกตเห็นได้ เพื่อตระหนักถึงข้อกำหนดเบื้องต้นเหล่านี้ วิทยานิพนธ์นี้จึงมุ่งเน้นที่จะวิเคราะห์ความซับซ้อนในการคำนวณสำหรับการวิเคราะห์ระดับการบาดเจ็บของอุบัติเหตุ โดยการพิจารณาการแปรเปลี่ยนชั่วคราวและการทดสอบปัจจัยเสี่ยงที่ส่งผลต่อระดับการบาดเจ็บของผู้ขับขี่รถยนต์และรถจักรยานยนต์ ด้วยการประยุกต์ใช้แบบจำลองเศรษฐมิติขั้นสูง **ส่วนแรกของวิทยานิพนธ์** มุ่งเน้นที่จะเป็นส่วนหนึ่งของการศึกษาด้านความปลอดภัยด้วยการตรวจสอบเชิงประจักษ์ ของการแปรเปลี่ยนแบบชั่วคราวของปัจจัย อันส่งผลต่อระดับการบาดเจ็บจากอุบัติเหตุแบบชนคันเดียว โดยการประยุกต์ใช้สองแบบจำลองขั้นสูง ได้แก่ การประยุกต์ใช้แบบจำลองความไม่สัมพันธ์ของพารามิเตอร์แบบสุ่ม ร่วมกับความแตกต่างในค่าเฉลี่ยและความแปรปรวน และแบบจำลองความสัมพันธ์ของพารามิเตอร์แบบสุ่ม ร่วมกับความแตกต่างในค่าเฉลี่ย **ส่วนที่สองของวิทยานิพนธ์** มุ่งเน้นที่จะทดสอบอย่างครอบคลุมสำหรับความแตกต่างของปัจจัยที่ส่งผลต่อระดับการบาดเจ็บของอุบัติเหตุ โดยการเปรียบเทียบระหว่างสาเหตุอุบัติเหตุจากการใช้ความเร็วเกินที่กฎหมายกำหนด และอุบัติเหตุที่เกิดจากสาเหตุอื่นๆ ด้วยการประยุกต์ใช้ความเป็นไปได้สำหรับการแปรเปลี่ยนชั่วคราว และความแตกต่างที่ไม่สามารถสังเกตได้ **ส่วนที่สามของวิทยานิพนธ์** มุ่งเน้นที่จะศึกษาความปลอดภัย โดยขยายการสืบสวนให้เป็นแบบเชิงลึก บนความแตกต่างของความรุนแรงของอุบัติเหตุที่เกิดขึ้น ระหว่าง วันธรรมดา วันหยุดสุดสัปดาห์ และวันหยุดนักขัตฤกษ์ พร้อมกับการวิเคราะห์ความแตกต่างที่ไม่สามารถสังเกตได้ ในส่วนนี้มีทดสอบการคาดการณ์นอกกลุ่มตัวอย่าง เพื่อที่จะเข้าใจความแตกต่างระหว่างปี และมีการคาดการณ์ความน่าจะเป็นของระดับความรุนแรงการบาดเจ็บของอุบัติเหตุรถจักรยานยนต์ ส่วนสุดท้ายคือ **ส่วนที่สี่ของวิทยานิพนธ์** มุ่งเน้นที่จะศึกษาความรุนแรงการบาดเจ็บของอุบัติเหตุรถจักรยานยนต์ โดยมุ่งเน้นที่จะศึกษาเปรียบเทียบความแตกต่างระหว่างอุบัติเหตุที่เกิดขึ้นเวลา

กลางวัน และเวลากลางคืน ซึ่งมีการพิจารณาความแปรเปลี่ยนแบบชั่วคราว วิทยานิพนธ์นี้ได้ดำเนินการที่ประโยชน์อย่างประจักษ์ อันจะเติมเต็มในการศึกษาด้านความปลอดภัย การทดสอบความแปรเปลี่ยนแบบชั่วคราว และความไม่แปรเปลี่ยนได้ถูกค้นพบในการศึกษานี้ โดยผลการศึกษาสามารถนำไปประยุกต์ใช้ในการกำหนดนโยบายเพื่อปรับปรุงความปลอดภัยทางถนนได้อย่างลึกซึ้ง นอกจากนี้ การค้นพบของวิทยานิพนธ์นี้ได้เสนอองค์ความรู้เชิงลึกสำหรับผู้ปฏิบัติงานด้านความปลอดภัย นักวิจัย เจ้าหน้าที่ของภาครัฐ และผู้ตัดสินใจกำหนดนโยบาย เพื่อที่จะนำไปใช้เพิ่มความปลอดภัยทางถนน และพัฒนาสิ่งอำนวยความสะดวกที่มีประสิทธิภาพมากยิ่งขึ้น สำหรับนโยบายที่บรรเทาความรุนแรงของอุบัติเหตุ

สาขาวิชา วิศวกรรมขนส่ง

ปีการศึกษา 2565

ลายมือชื่อนักศึกษา ....

ลายมือชื่ออาจารย์ที่ปรึกษา ....

CHAMROEUN SE : TEMPORAL STABILITY ANALYSIS IN ROADWAY CRASH INJURY SEVERITIES RESEARCH WITH UNOBSERVED HETEROGENEITY. THESIS ADVISOR : PROF. VATANAVONGS RATANAVARAHA, Ph.D., 281 PP.

Keyword: Driver Injury/Motorcyclist Injury/Single-Vehicle Crash/ Motorcycle Crash/ Temporal Stability/Unobserved Heterogeneity/Thailand

Development of the crash-injury severity models must address two issues: temporal shift of contributing factors and underlying unobserved heterogeneity in crash data. Recognizing these prerequisites, this dissertation contributes towards addressing the computational challenges in crash-injury severity analysis by considering temporal shift and examining risk factors affecting driver- and motorcyclist-injury severity, utilizing the advanced econometric crash severity modelling approaches. **The first part of the dissertation** contributes to safety literature by empirically investigating the temporal stability of factors influencing driver-injury severities in single-vehicle crashes using two advanced heterogeneity models—Uncorrelated random parameters with heterogeneity in means and variances approach and Correlated random parameters with heterogeneity in means approach). **The second part of the dissertation** comprehensively examines the differences between factors associated with speeding driving-related crashes and non-speeding driving crashes on the outcomes of driver-injury severity by carefully accounting for possible temporal shift and unobserved heterogeneity. **The third part of the dissertation** contributes to the safety literature by extensively conducting an in-depth investigation on the differences between weekday, weekend, and holiday motorcyclist injury severity alongside a temporal instability investigation while also accounting for unobserved heterogeneity. In this part, out-of-sample prediction simulations are additionally run to clearly understand the difference between each time-of-year (weekdays, weekends, and holidays) and between each year motorcyclist-injury severity predicted probabilities. Lastly, **the fourth part of the dissertation** contributes to motorcyclist safety literature by uncovering possible daytime and nighttime variation and temporal

shift on resulting motorcyclist injury severities. The current dissertation produces substantial empirical contributions to the existing safety literature. The temporal instability and nontransferability found in this dissertation have profound implications for the current safety practice and allocation of funds for safety improvements. In addition, the findings of the dissertation would indeed provide valuable knowledge for practitioners, researchers, institutions, and decision-makers to enhance highway safety and facilitate the development of more effective crash injury mitigation policies.

School of Transportation Engineering　　Student's Signature ....

Academic Year 2022　　Advisor's Signature ....

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SYMBOLS AND ABBREVIATIONS

S, Y	=	Severity function
β	=	Vector of estimable coefficient
X	=	Vector of explanatory variable
ε	=	Error term
P	=	Probability function
$f(\boldsymbol{\beta}\|\rho)$	=	Density function
Z	=	Explanatory variable capturing heterogeneity in the mean
$\boldsymbol{\Theta}, \boldsymbol{\delta}$	=	Vector of estimable parameters *Z*
$\boldsymbol{W}$	=	Explanatory variable capturing heterogeneity in the variance
σ	=	Standard deviation of random parameter
$\boldsymbol{\omega}$	=	Vector of standard deviation of random parameter (bold letter)
ν	=	Disturbance term
η	=	Vector of estimable parameters *Z*
Γ	=	Symmetric Cholesky matrix
ω	=	Randomly distributed term with mean = 0 and variance = σ^2
SE	=	Standard Error
$S_{\sigma_{rn}}$	=	Standard deviation of the observation-specific σ_{rn}
N	=	Number of observations
t_{σ_r}	=	t-statistic of the correlated random parameters
Cor	=	Correlation coefficient between two random parameters
cov	=	Covariance between two random parameters
r	=	Random parameter
χ^2, X^2	=	Chi-square likelihood ratio test
LL(β)	=	Log-likelihood at convergence of the function
LL(0)	=	Log-likelihood at zero parameter
LL(Constant)	=	Log-likelihood with “one” as a parameter
dof	=	degree of freedom

SYMBOLS AND ABBREVIATIONS (Continued)

ρ^2	=	McFadden R-square value
ME	=	Marginal effect
μ	=	Estimated threshold
$\Phi(.)$	=	Cumulative standard normal distribution
$\mathbf{\Omega}$	=	Explanatory variable capturing heterogeneity in the mean
$\boldsymbol{\psi}$	=	Vector of estimable parameters $\mathbf{\Omega}$
$\mathbf{\Psi}$	=	Explanatory variable capturing heterogeneity in the variance
$\boldsymbol{\gamma}$	=	Vector of standard deviation of random parameter
ω	=	Disturbance term (not bold letter)
S.D. (or SD)	=	Standard deviation of variable
Std	=	Standard deviation of variable
WHO	=	World Health Organization
NHTSA	=	National Highway Traffic Safety Administration
HAIMS	=	Highways Accident Information Management System
DOH	=	Department of Highways
RTC	=	Road Traffic Crashes
RTI	=	Road Traffic Injuries

CHAPTER I

INTRODUCTION

1.1 Motivations of the Study

Road traffic crashes certainly remain a serious public health burden causing huge numbers of avoidable deaths and disabilities, with over 1.3 million people killed and up to 50 million injured globally every year (WHO, 2017). The resulting injuries from this road trauma has momentous consequences—by way of illustration, extra burden on health systems, countries' economic loss, loss of human resources, and untold or unseen misery and economic consequences to families whose lives have to put up with bereavement or disabled relative (Bryant et al., 2004; Masilkova, 2017; Mayou and Bryant, 2003; Mitchell, 1997; WHO, 2017). Approximately 90% of the total injuries and fatalities occur in low- and middle-income countries (LMIC). Particularly in the Southeast Asia region, the death rate due to roadways crashes is approximately 316, 000 victims per year, and the so-called vulnerable road users such as pedestrians, cyclists and motorcyclists constitute up to 50% of deaths on the road in the Region (WHO, 2017). The remaining parts of this subsection will provide a rationally brief discussion of two major issues that significantly contribute to the observed resulting injuries and fatalities rates in the context of a middle-income developing country from Southeast Asia region—Thailand.

First issue: based on the crash data statistics from the Department of Highways [DOH] from 2011 to 2017, single-vehicle run-off-road crashes make up approximately 52% of the total number crashes in Thailand. Over the same year period, not only the frequency rate of single-vehicle crashes but also fatalities associated with this crash type are on an increasing trend compared with previous years (Se et al., 2020). In addition, compared with fatalities rate resulting from other crash types (i.e., rear-end, pedestrians, head-on, and sideswipe crashes), the rate of driver fatalities in single-vehicle crashes remains the highest (Champahom et al., 2020). These circumstances necessitate a comprehensive research to better understand risk factors associated with driver-injury severities involving in single-vehicle crashes.

Second issue: examining the deaths rate by road user category based on a World Health Organization report in 2016, motorcycle riders were approximately over 74% of the total fatalities due to roadway crashes on Thailand roadways—the highest compared to other road-user categories. In 2018, on the world's list of most dangerous roads, even though Thailand's rank has dropped from second to ninth, road traffic deaths among motorcyclists in Thailand are still the highest in the world (WHO, 2018). These situations entail an in-depth research concerning the resulting injury severities of crashes involving motorcycle users, which also requires further investigation to provide insightful knowledge for developing appropriate and targeted strategies for crash mitigation and prevention.

1.2 Temporal instability in Crash-Injury Severity Analysis

Temporal stability investigation is an important assessment that may have profound impact on safety countermeasures. That is, if the effects of the contributing factors are temporally unstable, it would not be possible to determine how much the implementation of specific safety countermeasures contributes to the changes in the severity of crashes (Behnood and Mannering, 2015). Mannering (2018) conducted a detailed discussion on temporal instability and analysis of highway accident data. The study pointed out that, in the past few decades, researchers and safety analysts have struggled to explain two longer-term phenomena: the general downward trend in fatalities per distance driven over time in most industrialized countries (developed countries), and the fact that fatalities per distance driven tend to decline in economic downturns and increase in economic upturns. The general downward trend has often been attributed to improvement in vehicle-safety technologies, highway design, impaired driver enforcement, and driver/public safety-education programs, etc. And, the effect of an adverse economy on fatalities per mile driven has been attributed to factors such as changes in discretionary driving patterns, values of time, the distances risky versus safe drivers drive, and so on. The temporal elements associated with individual behavior and the aggregate trends that result from the above-mentioned issues are important factors to consider when developing modeling approaches and interpreting model findings. In sum, ignoring these fundamental temporal elements can lead to erroneous conclusions and ineffective or even dangerous safety policies.

In recent years, the temporal factor (time period of crash occurrence) has been recognized as an important matter in crash-injury severity research and has been regarded as a major source of unobserved heterogeneity. When comparing the present time to years ago (e.g. five or more year ago), the improvement of traffic crash associated fatalities can be observed and may possibly be attributed to a design and enforcement of several policies such as mandatory seat belt use, vehicle regulations requiring airbag, child rear facing seats, advance in vehicle technology to improve occupant safety and concerted effort dedicated to education awareness campaigns for different driver age groups to encourage safe driving behavior (Marcoux et al., 2018). Behnood and Mannering (2015) also pointed out another important source of temporal instability in their crash severity studies. That is, although officers are trained for consistency in their reporting, there could be potential changes in police-reporting practice over time such as opinions relating to the primary cause of the crash, the apparent condition of the driver, etc. These issues could give the appearance of temporal instability with regard to crash determinants. Owing to the necessity to account for temporal shift, numerous studies have empirically investigated the temporal stability of factors impacting the crash injury severities and have indeed provided valuable insight into better understanding of effect determinants over times (Al-Bdairi et al., 2020; Alnawmasi and Mannering, 2019, 2022; Alogaili and Mannering, 2022; Behnood and Mannering, 2019; Behnood and Mannering, 2015, 2016; Dabbour, 2017; Dabbour, et al., 2020; Dabbour, et al., 2019; Islam et al., 2020; Islam and Mannering, 2020; Li et al., 2019; Yan et al., 2022; Yu et al., 2020; Zamani et al., 2021).

1.3 Unobserved Heterogeneity in Crash-Injury Severity Analysis

Mannering et al. (2016) have provided a robust review on why accounting for unobserved heterogeneity (simpler term: unobserved effect, unobserved factor, or unobserved characteristic) is empirically necessary. The unobserved heterogeneity refers to unavailable attributes that are not able to be captured in the real time data.

These unobserved attributes may be the results of genders' physiological variation, physical characteristics variation, variation in the effects of different number of passengers, vehicle-type designations variation, effectiveness of vehicle safety features variation relative to the physical characteristics of the occupant, variation in roadway characteristics from one road segment to the next and variation in environmental and temporal characteristics (e.g., time-of-day, day of the week, presence of rain, snow, and lighting conditions).

Methodological speaking, the said unobserved heterogeneity may not be fully captured using only standard ordered or unordered discrete choice modelling approaches in the existing crash data. To address this issue, Mannering et al. (2016) have also reviewed and recommended several advanced econometric approaches that can be used to deal with it—among them, various extensions of the random parameters modeling technique sound very promising in addressing unobserved heterogeneity in a more flexible way.

1.4 Purpose of the Research

Despite the progress of research effort made over the years, there is further scope for improving road safety for all road users. Given that the single-vehicle crashes have the highest frequency rate and motorcyclist has the highest mortality rate, the purpose of this dissertation is to study temporal instability of significant risk factors (how each risk factor changes varies over times period) affecting driver-injury severity in single-vehicle crashes and motorcyclist-injury severity in crashes involving motorcycle. Specifically, the main objectives are:

I. Investigate temporal instability of affecting factor of driver-injury severity in single-vehicle crashes.

II. Comparing temporal instability of risk factors associated with driver-injury severity involving speeding-driving and non-speeding driving crashes.

III. Study Day-of-week and holidays variations and temporal instability of determining factors of motorcyclist injury-severity.

IV. Study time-of-day variations and temporal instability of determining factors of motorcyclist injury severity.

1.5 Scope of the Research

The scopes of this research are as follows:

I. Utilizing single-vehicle crashes data between 2011-2017 and motorcycle crashes data between 2016-2019 obtained from Highways Accident Information Management System (HAIMS), under Department of Highways (both datasets are the latest available data).

II. Using advanced statistical and econometric approaches for each research objective (i.e., proposed research papers).

III. Fully accounting for unobserved heterogeneity in crashes severity modeling.

IV. Fully accounting for temporal influence/shift in crashes severity modeling.

1.6 Research Questions

This research has the following research questions:

I. Why is each objective potentially crucial for improving road safety?

II. What is the appropriate statistical method for analyzing data of each objective?

III. What contributing factors have heterogeneous effects on resulting injury severities?

IV. What are the differences in the impact degree of factors between the separated models?

V. Are the effects of risk factors impacting injury severities of the crashes temporally stable?

1.7 Contributions of the Research

The contributions of this research are as follows:

I. Identifying statistically significant risk factors affecting crashes-injury severity could potentially assist policymaker/safety professionals and practitioners/trainer/government agency/highway designer in future planning and serve as guidance for mitigation policies directed at safety improvement for both driver and motorcyclist.

II. Temporal instability of significant risk factors can help decision-maker to better understand the changes in effect of human factor, vehicle technology, roadway improvement, macroeconomic condition and other information technology on crash-injury severity. With this expected insightful knowledge, decision-maker could have a better understanding of stability of each risk factor effect over time which could assist in selecting the most effective countermeasures.

III. Identification of quantified effects of significant risk factors over time can be used in cost-benefit analysis to determine if investment in certain countermeasure implementations is effective or not.

1.8 Organizations of the Thesis

This dissertation is divided into 6 chapters as follows: **Chapter I:** Introduction, **Chapter II:** Temporal Stability of Factors Influencing Driver-Injury Severities in Single-Vehicle Crashes: A Correlated Random Parameters with Heterogeneity in Means and Variances Approach, **Chapter III**: Analysis of driver-injury severity: a comparison between speeding and non-speeding driving crash accounting for temporal and unobserved effects, **Chapter IV**: The impact of weekday, weekend, and holiday crashes on motorcyclist injury severities: accounting for temporal influence with unobserved effect and insight from out-of-sample prediction, **Chapter V**: Day and Night Variation of Factors Impacting Motorcyclist Injury Severities: Accounting for Potential Temporal Shifts and Unobserved Effects, and **Chapter VI**: Conclusion and recommendations.

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CHAPTER II

TEMPORAL STABILITY OF FACTORS INFLUENCING DRIVER-INJURY SEVERITIES IN SINGLE-VEHICLE CRASHES: A CORRELATED RANDOM PARAMETERS WITH HETEROGENEITY IN MEANS AND VARIANCES APPROACH

2.1 Abstract

Undoubtedly, single-vehicle crashes remain a major concern for roadway users and highway administrators, especially in low- and middle-income developing countries, where accident death rates remain extremely high. This study investigated the temporal instability of contributing factors of driver-injury severities in single-vehicle crashes using data in Thailand, a developing country, from 2011 to 2017. The uncorrelated and correlated random parameters model, which enable a possible heterogeneity in means and variances approaches, were estimated for individual year model using two levels of driver-injury severities, namely, no/minor injury and severe/fatal injury. The models considered a wide range of factors, such as driver, roadway, vehicle, crash, environmental and temporal, and spatial characteristics. The series of likelihood ratio test and the marginal effect of significant factors were computed to explore the temporal stability of the year models and to investigate the temporal instability of the effect of each parameter estimate on the probability of driver-injury severities within given time periods, respectively. The result indicates that a substantial temporal instability exists in the model specifications and estimated parameters (temporally unstable factor included male driver, driving using exceeding speed limit, crashes on asphalt pavement, crashes on weekends, and crashes on weekend during nighttime with present of road lighting) across the time periods under study (despite insignificant in particular year models, some factors were stable but marginal effects varied across time). The findings may be used to assist and guide decision makers in policy generation for plans to mitigate driver-injury severities.

Despite the unclear source of temporal instability, the finding emphasizes the importance of the temporal instability of the factors that influence the outcomes of driver-injury severities. Alternatively, ignoring temporal instability in studies on crash severity may lead to high levels of bias and inaccurate conclusions. With regard to methodologies, both random parameters with heterogeneity in means and variances and correlated random parameters with heterogeneity in means approaches are promising methods with ability to offer another layer of insight into unobserved heterogeneity in injury severities research.

2.2 Introduction

Single-vehicle crashes worldwide constitute the highest rate of accidents and account for the majority of serious and fatal crashes (Al-Bdairi and Hernandez, 2017; Hou et al., 2019; NHTSA, 2016). Despite the number of developed countries that achieved success in reducing road traffic death in the past several years, progress continues to vary significantly across the world. The risk of road traffic death is more than three times higher in low- and middle-income countries (an average of 27.5 per 100,000 population) than high-income countries (an average of 8.3 per 100,000 population) (World Health Organization [WHO], 2018). As a middle-income and developing country, Thailand encounters tremendous economic and emotional burdens due to road accidents with a death rate of 32.8 per 100,000 population (WHO, 2018). In addition, approximately 52% of road accidents are single-vehicle crashes (data derived from the Department of Highways [DOH] from 2011 to 2017). Moreover, increases in the occurrence rates of single-vehicle crashes and fatalities are observed compared with previous years (Se et al., 2020a). With the rate of driver fatalities in single-vehicle crashes remaining the highest compared with other crash types (i.e., rear-end, pedestrians, head-on, and sideswipe crashes) (Champahom et al., 2020), a clear need exists to extensively study driver-injury severities in single-vehicle crashes.

The abovementioned variation in the trends of fatality rates may be due to changes in the effect of factors influencing injury severities due to crashes over time. Such issues regarding temporal instability has gained increased attention from frontline studies on injury severities that intend to optimize accuracy and provide reliable conclusions (i.e., single-vehicle (Behnood and Mannering, 2015; Dabbour et al., 2019; Yu et al., 2020, 2021), rear-end (Dabbour et al., 2020), large-truck (Behnood and Mannering, 2019), aggressive and non-aggressive driving (Islam and Mannering, 2020), pedestrian-injury (Behnood and Mannering, 2016; Li et al., 2021), motorcycle (Alnawmasi and Mannering, 2019), animal-vehicle (Al-Badairi et al., 2020), and work-zone (Islam et al., 2020) crashes). Research has recently recognized the influence of temporal instability on injury severities as an essential issue and one of the major sources of unobserved heterogeneity in studies on traffic safety that requires careful investigation (Mannering et al., 2016). Over the years, significant improvements have been observed in fatalities and severe injuries associated with crashes that can be attributed to various factors, such as policy enforcement, enhanced safety features and technology of vehicles, and education campaign efforts to promote safety (Marcoux et al., 2018). Another important source of temporal instability has been related to changes in practices of data collection over time (for details, see Behnood and Mannering (2015)). Therefore, disregarding the influence of temporal instability on levels of crash injury severities may lead to bias and inaccurate or unreliable results and conclusions (Al-Bdairi et al., 2020; Behnood and Mannering, 2015; Mannering, 2018; Yu et al., 2020). **Table 2.1** provides a summary of previous studies that investigated temporal stability in terms of injury severities studies. Such studies used data from states of a developed country (USA). In addition, the table indicates that a considerable number of significant explanatory variables become unstable over time, which may be explained by changes in individual behaviors, attitudes toward safety, macroeconomics, and improvement in the safety features of vehicles.

In this regard, the current study is novel as it specifically focuses on the temporal stability of contributing factor of driver-injury severities in single-vehicle crashes in the context of a developing country. The primary objective of the study is to comprehensively investigate the temporal stability of effects of contributing factors, such as driver, vehicle, roadway, crash, environmental and temporal, and spatial characteristics, on driver-injury severities in single-vehicle crashes using accidents data in Thailand. The unique contributions of the study are as follows: (1) develop different sets of observations, which may feature specific parameter distributions as a result of varying levels of driver-injury severities, (2) provide in-depth analysis of the influencing factors of driver-injury severities in single-vehicle crashes in Thailand, and (3) offer in-depth understanding of the stability of various factors and possible reasons behind the unstable factors of driver-injury severities over time through the findings, which can serve as reference for policy makers in developing efficient and effective safety countermeasure to mitigate severe or fatal injuries among drivers. Moreover, the study adds to the growing literature by contributing to the knowledge on the degrees of the temporal instability of the influencing factors of driver-injury severities in single-vehicle crashes

2.3 Methodology

The researches on accident injury severities commonly use two main approaches, namely, ordered-and unordered discrete outcome approaches from standard logit/probit models to sophisticated heterogeneity models (i.e., finite mixture and random parameter models). Over the years, the majority of recent frontline research focused on advanced statistical and econometric approaches that consider unobserved heterogeneity and intend to minimize biases and erroneous inferences, which may lead to the effective implementation of countermeasures. Such approaches include mixed logit model (random parameter model) (Anastasopoulos and Mannering, 2011; Al-Bdairi and Hernandez, 2017; Behnood and Mannering, 2015, 2016, 2017; Cerwick et al., 2014; Li -et al., 2019a, 2019b; Liu and Fan, 2020; Rezapour et al., 2019; Ye and Lord, 2014), latent class model (finite mixture model) (Behnood and Mannering, 2016; Behnood et al., 2014; Cerwick et al., 2014; Li et al.,2019a, 2019b; Liu and Fan, 2020; Shaheed and Gkritza, 2014), finite mixture model with random parameters (Li et al., 2018; Xiong and Mannering, 2013; Yu et al., 2019), random parameters model allowing possible heterogeneity in means and variances approach (Al-Bdairi et al., 2020; Alnawmasi and Mannering, 2019; Behnood and Mannering, 2019; Islam et al., 2020; Islam and Mannering, 2020; Li et al., 2021), correlated random parameters (Ahmed et al., 2020; Fountas and Anastasopoulos, 2018; Fountas et al., 2018a), correlated random parameters model with heterogeneity in means (Ahmed et el., 2021).

Table 2.1 Summaries of previous temporal stability studies on injury severity

Authors and considered crash type	Methodological Approach	Geographical context and data period	Temporal instability finding
Behnood and Mannering (2015) Single-vehicle crashes	Mixed logit model	Chicago 2004–2012	The study pointed out that improvement in vehicle safety features, drivers' response to these improvements, drivers' response to changes in macroeconomic condition, and other factors (i.e., gender, physical condition, vehicle occupancy, road surface, weather, and light condition) may be potential causes of temporal instability of the models for driver crash severity.
Behnood and Mannering (2016) Pedestrian-injury crashes	Latent-class logit and mixed logit model	Chicago 2005–2012	Despite unclear sources for the observed temporal instability, the study pointed out that the increased fraction of pedestrian fatalities and its finding on temporal instability are consistent with an unfortunate consequence of continuous improvements in the safety features of vehicles.

Table 2.1 Summaries of previous temporal stability studies on injury severity (Cont.)

Authors and considered crash type	Methodological Approach	Geographical context and data period	Temporal instability finding
Alnawmasi and Mannering (2019) Single-vehicle motorcycle crashes	Random parameters model with heterogeneity in the means and variances	Florida 2012–2016 (newly licensed driver in 2012) 2005–2015 (crashes on horizontal curve)	The study found a significant temporal instability in motorcyclist injury, which was likely due to changes in motorcycle technology and performance, changes in macroeconomic conditions, changes induced by the response of riders to the changing behavior of other road users, and changes in riders' behavior and skills over time
Dabbour et al., (2019) Single-vehicle crashes	Ordinal regression and random parameters ordered logit	North Carolina 2007–2013	The results of this study indicated that if safety treatments were applied by considering only the overall models without investigating the temporal stability of the identified factors, then determining whether any potential safety improvement is attributed to the applied safety treatments or the temporal instability of the identified factors is difficult.

Table 2.1 Summaries of previous temporal stability studies on injury severity (Cont.)

Authors and considered crash type	Methodological Approach	Geographical context and data period	Temporal instability finding
Behnood and Mannering (2019) Large-truck crashes	Random parameters model with heterogeneity in the means and variances	Los Angeles 2010–2017	The finding indicated that the instability of the effect of contributing factors on injury severity from large-scale crashes exists across daily time periods (i.e., morning [6:00–11:59] and afternoon [12:00–5:59]) and across years. The finding also emphasized the importance of the time-dependence effect exerted by variables on resultant injury-severity outcomes in crashes involving large trucks
Yu et al., (2020) Run-off-road crashes	Random parameter ordered probit model with heterogeneity in mean	North Carolina 2014–2017	Indicators, such as involvement of alcohol, passenger car, pick-up truck, sport utility vehicle, wet surface condition, ice/snow condition, and curved roadway, exhibited relatively stable effects over time, whereas indicator, such as fatigue driving, speed limit (35–55 mph), urban area, clear condition, and median width, exerted varied effects on driver-injury severity over time.

Table 2.1 Summaries of previous temporal stability studies on injury severity (Cont.)

Authors and considered crash type	**Methodological Approach**	**Geographical context and data period**	**Temporal instability finding**
Islam and Mannering (2020) Work-zone crashes	Random parameters model with heterogeneity in the means and variances	Florida 2012–2017	The model estimation results of the study illustrated a significantly fundamental shift in unobserved heterogeneity, which generates statistically significant temporal instability of the contributing factors over the period considered. The unique set of work zone characteristics and changes in the sample of work zones on a yearly basis (i.e., highway maintenance and construction are undertaken in different locations) could be a substantial source of the observed temporal instability
Islam and Mannering (2020) Aggressive and non-aggressive driving	Random parameters model with heterogeneity in the means and variances	Florida 2015–2017	The study revealed that the marginal effect of many contributing factors in crashes involving non-aggressive drivers were relatively stable over time, whereas only restraint usage exhibited stable marginal effects in crashes involving aggressive drivers.

Table 2.1 Summaries of previous temporal stability studies on injury severity (Cont.)

Authors and considered crash type	Methodological Approach	Geographical context and data period	Temporal instability finding
Al-Badairi et al., (2020) Animal-vehicle crashes	Random parameters model with heterogeneity in the means and variances	Washington 2012–2016	The study also revealed a number of influencing factors that were temporally unstable due to various factors, such as changes in individual behaviors, information processing, risk assessment, and safety attitudes toward changes in information technologies, communication, and vehicles. In addition, the finding underscored the temporal instability of factors influencing injury severity.
Yu et al., (2021) Run-off-road crashes	Random thresholds random parameters hierarchical ordered probit	North Carolina 2014–2017	The explanatory variables with relatively stable effects over time were alcohol involvement, curved roadway, passenger car, SUV, and wet/water surface, whereas the variables female driver, speed limit (35–55 mph), AADT (>25,000), and collector displayed unstable effects over time.

Table 2.1 Summaries of previous temporal stability studies on injury severity (Cont.)

Authors and considered crash type	Methodological Approach	Geographical context and data period	Temporal instability finding
Li et al., (2021) Pedestrian-vehicle crashes	Random parameters model with heterogeneity in the means and variances	North Carolina 2007–2018	This result implied that only two indicators (i.e., ambulance rescue and curved roadway) generate temporally stable effects on pedestrian injury severity, whereas all other factors produce strong temporal instability across the three-year period and according to the day of the week.

The current study employs random parameters model that considers a possible heterogeneity in means and variances and correlated random parameters with heterogeneity in means (empirically explores when two or more random parameters are found to be statistically significant) to address possible unobserved heterogeneity. Initially, for random parameters model allowing possible heterogeneity in means and variances, the model estimation introduces a function that determines the probability of driver-injury outcomes, which is defined as follows (Washington et al., 2020),

$$S_{jm} = \boldsymbol{\beta}_j \boldsymbol{X}_{jm} + \varepsilon_{jm}, \tag{2.1}$$

where S_{jm} denotes an injury severities function that determines the probability of the levels of driver-injury severities j in crash m, $\boldsymbol{\beta}_j$ pertains to the vector of estimable coefficients, $\boldsymbol{X}_{jm}$ represents the vector of explanatory variables (i.e., driver, roadway, crash, vehicle, environment and temporal, and spatial attributes) that impact injury severities, and ε_{jm} stands for the error term. Taking into account crash-specific unobserved heterogeneity, the outcome probabilities of a random parameter logit model of driver-injury severities in single-vehicle crashes, can be defined as (Washington et al., 2020),

$$P_m(j) = \int \frac{EXP(\boldsymbol{\beta}_j \boldsymbol{X}_{jm})}{\sum_{\forall j} EXP(\boldsymbol{\beta}_j \boldsymbol{X}_{jm})} f(\boldsymbol{\beta}|\rho) d\,\boldsymbol{\beta}, \tag{2.2}$$

where $P_m(j)$ stands for the probability of injury severities j in crash m, $f(\boldsymbol{\beta}|\rho)$ refers to the density function of $\boldsymbol{\beta}$ with ρ being vector of parameters (mean and variance), and all other terms are as previously defined. To account for possibility of unobserved heterogeneity in the means and variances of random parameters, let $\boldsymbol{\beta}_{jm}$ be a vector of estimated parameters that varies across crashes, which are derived as follows (Washington et al., 2020),

$$\boldsymbol{\beta}_{jm} = \boldsymbol{\beta}_j + \Theta_{jm}\boldsymbol{Z}_{jm} + \sigma_{jm} EXP(\boldsymbol{\omega}_{jm}\boldsymbol{W}_{jm})\nu_{jm}, \tag{2.3}$$

where $\boldsymbol{\beta}_j$ refers to the mean parameter estimate across all crashes, $\boldsymbol{Z}_{jm}$ is a vector of the explanatory variable that capture heterogeneity in the mean that influence driver-injury severities level j, Θ_{jm} represents a vector of estimable parameters, $\boldsymbol{W}_{jm}$ refers to a vector of crashes-specific variables that captures heterogeneity in the standard deviation σ_{jm} with corresponding vector $\boldsymbol{\omega}_{jm}$, and disturbance term is denoted by ν_{jm}.

For model with two or more statistically significant random parameters, the correlated random parameters model was empirically tested which is applied to the logit model as follow (Ahmed et al., 2021; Fountas et al., 2018a; Washington et al., 2020),

$$\beta_m = \boldsymbol{\beta} + \eta Z_m + \Gamma\omega_m, \tag{2.4}$$

where $\boldsymbol{\beta}$ is the mean value of the random parameter vector, Z_m is the vector of explanatory variables influencing the mean of β_m, η is the vector of estimable parameters corresponding to Z_m. Γ denotes a symmetric Cholesky matrix which is used to compute the standard deviation of the random parameters, and ω_m denotes a randomly distributed term with mean value of zero and variance equal to σ^2. And standard deviation of the correlated random parameters is based on the diagonal and off-diagonal elements of the Γ matrix which can be defined as (Washington et al., 2020),

$$\sigma_r = \sqrt{\sigma_{k,k}^2 + \sigma_{k,k-1}^2 + \sigma_{k,k-2}^2 + \cdots + \sigma_{k,1}^2}, \quad (2.5)$$

where σ_r denotes the standard deviation of the random parameter r, $\sigma_{k,k}$ is the Γ matrix's respective diagonal element, and $\sigma_{k,k}$, $\sigma_{k,k-1}$ $\sigma_{k,k-2}$,... $\sigma_{k,1}$ denotes the lower triangular matrix's off-diagonal elements corresponding to the random parameter r. And for each correlated random parameter, standard error and t-statistic of the standard deviation σ_{rn} are computed as (Washington et al., 2020),

$$SE_{\sigma_r} = \frac{S_{\sigma rn}}{\sqrt{N}}, \quad (2.6)$$

where $S_{\sigma_{rn}}$ is the standard deviation of the observation-specific σ_{rn}, and N is the total number of observations in the model estimation, and,

$$t_{\sigma_r} = \frac{\sigma_r}{SE_{\sigma_r}}, \quad (2.7)$$

This t-statistic serves the purpose whether the standard deviations of the correlated random parameters are statistically different form zero. And lastly, the correlation coefficient between two random parameters is derived as (Fountas et al., 2018b),

$$Cor(x_{r,n}, x_{r',n}) = \frac{cov(x_{r,n}, x_{r',n})}{\sigma_{r,n}, \sigma_{r',n}}, \quad (2.8)$$

where $cov(x_{r,n}, x_{r',n})$ is the covariance between the two variables with random parameters r and r', and $\sigma_{r,n}$ and $\sigma_{r',n}$ are their standard deviation, respectively.

The study employed simulated maximum likelihood estimation with 1000 Halton draws to generate stable parameters (McFadden and Train, 2000; Bhat, 2001; Train, 2009; Alnawmasi and Mannering, 2019; Islam et al., 2020), whereas normal distribution was considered for the function form of parameter density function $f(\beta|\varphi)$ because it generally provides the best fit for data on injury severities (Al-Bdairi et al., 2020; Behnood and Mannering, 2016; Shaheed et al., 2013). In addition, the study computed average marginal effect over all crash observations to capture the effect that a one-unit change in any specific explanatory variable has on the probability of an injury severity outcome (i.e., for indicator variables this is the change in probability resulting from the indicator going from zero to one; see Washington et al., 2020 and Islam et al., 2020). This study used NLOGIT 6 software for statistical analyses.

2.4 Empirical Setting

The current study obtained the latest available data for single-vehicle crashes across seven years (January 1st 2011–December 31st 2017) from the Highways Accident Information Management System, Thailand (DOH, 2018). The total cases of single-vehicle crashes during this period reached 9,788. The data provided comprehensive information, which was further coded into a series of variables and classified into six groups of characteristics, namely, (1) driver (i.e., age, gender, if a driver is fatigued, drunk, or exceeding the speed limit and seatbelt usage), (2) roadway (i.e., median type, number of traffic lanes, pavement type, status of construction or maintenance, curve road, graded road, intersection, and U-turn), (3) vehicle type, (4) crash (off-road on straight, off-road on curve, off-road and hit guardrail, and mounts traffic island), (5) environmental and temporal (i.e., wet road, weather condition, light condition, weekend, morning peak hours, and evening peak hours), and (6) spatial characteristic (i.e., central, eastern, northern, and southern parts of the country). In the original report, the police officer cited four levels of driver-injury severity, namely, minor injury (or no injury), severe injury, death at the accident point, and death upon arrival at the hospital. However, to overcome issues related to the limited number of fatalities and difficulty in distinguishing between severe injuries and fatalities, the study combined severe and fatal injury (Ahmed et al., 2018; Zubaidi et al., 2021). In this study, no/minor injury outcome is coded as "0" and severe/fatal injury outcome is coded as "1" (**Table 2.2**).

2.5 Temporal Stability Test

To statistically test if the models for driver-injury severities are temporally stable in general, two series of temporal stability tests were conducted. First, likelihood ratio tests were used to compare the model developed for two individual years and determine whether the parameter estimates were stable between the two years. The test is given as follows (Washington et al., 2020),

$$\chi^2 = -2[\mathrm{LL}(\beta_{m_2 m_1}) - \mathrm{LL}(\beta_{m_1})], \tag{2.9}$$

where $\mathrm{LL}(\beta_{m_2 m_1})$ is the log-likelihood at the convergence of the model containing significant (converged) parameters from m_2 and using data subset m_1 at the same time. $\mathrm{LL}(\beta_{m_1})$ pertains to the log-likelihood at the convergence of the model using data from subset m_1 with parameters no longer restricted to the converged parameters of subset m_2. The test was also reversed, such that subset m_1 became m_2 and vice versa. To determine the confidence level, χ^2 statistic with a degree of freedom equal to the number of estimated parameters is used on the basis of the rejection or acceptance of the null hypothesis that the parameters are the same between time periods m_1 and m_2.

Secondly, temporal stability was verified using the transferability test to identify the necessity of separating the model by year or not. Transferability was tested using the likelihood ratio, which is derived as follows (Washington et al., 2020),

$$\chi^2 = -2\mathrm{LL}[(\beta_{2011-2017}) - \mathrm{LL}(\beta_{2011}) - \mathrm{LL}(\beta_{2012}) - \mathrm{LL}(\beta_{2013}) - \mathrm{LL}(\beta_{2014}) - \mathrm{LL}(\beta_{2015}) - \mathrm{LL}(\beta_{2016}) - \mathrm{LL}(\beta_{2017})], \tag{2.10}$$

Table 2.3 presents the series of results of the likelihood ratio test calculated using Eq. (2.9). The 38 tests produce a confidence level more than 99% (except for m_2/m_1 for 2017/2011, 2017/2012, 2017/2014 and 2017/2016 which produce less than 99% confidence level; however, the reversed tests of these models produce 99% confidence level). The results indicate that the null hypothesis (the effects of the explanatory

Table 2.2 Descriptive statistic of the variable used in the estimations

Variables	2011		2012		2013		2014		2015		2016		2017	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Injury severities														
No and Minor/severe and fatal injury (frequency)	739/338		904/338		968/382		1179/450		1246/466		618/211		1456/582	
Driver Characteristics														
Young-driver indicator (1 if a driver is aged below 26, 0 otherwise)	0.101	0.302	0.114	0.318	0.078	0.268	0.382	0.486	0.125	0.331	0.118	0.323	0.223	0.417
Old-driver indicator (1 if a driver is aged 50 years and above, 0 otherwise)	0.120	0.325	0.243	0.429	0.069	0.253	0.128	0.335	0.232	0.423	0.088	0.284	0.242	0.428
Gender indicator (1 if male driver, 0 female driver)	0.865	0.341	0.866	0.341	0.880	0.325	0.866	0.341	0.871	0.335	0.872	0.334	0.889	0.315
Restrain indicator (1 if a driver uses seatbelt, 0 otherwise)	0.401	0.490	0.398	0.490	0.390	0.488	0.399	0.490	0.407	0.491	0.416	0.493	0.382	0.486
DUI indicator (1 if a driver is under influence of alcohol, 0 otherwise)	0.017	0.128	0.016	0.126	0.019	0.135	0.018	0.132	0.020	0.142	0.016	0.124	0.016	0.124
Speed indicator (1 if a driver exceeds speed limit, 0 otherwise)	0.782	0.413	0.791	0.407	0.755	0.430	0.777	0.416	0.783	0.412	0.800	0.400	0.768	0.422
Fatigue indicator (1 if a driver falls asleep, 0 otherwise)	0.121	0.326	0.115	0.319	0.119	0.324	0.122	0.327	0.120	0.325	0.101	0.302	0.132	0.339
Roadway Characteristics														
Painted median indicator (1 if a crash occurs on painted median road, 0 otherwise)	0.032	0.177	0.036	0.187	0.033	0.178	0.048	0.214	0.048	0.214	0.037	0.190	0.057	0.233
Raised median indicator (1 if a crash occurs on raised median road, 0 otherwise)	0.309	0.462	0.282	0.450	0.266	0.442	0.251	0.434	0.252	0.434	0.247	0.432	0.235	0.424
Depressed median indicator (1 if a crash occurs on depressed median road, 0 otherwise)	0.331	0.471	0.358	0.480	0.370	0.483	0.343	0.475	0.336	0.473	0.384	0.487	0.361	0.480
Barrier median indicator (1 if a crash occurs on barrier median road, 0 otherwise)	0.032	0.177	0.027	0.161	0.027	0.161	0.042	0.200	0.055	0.229	0.062	0.240	0.057	0.233
Two-lane indicator (1 if a crash occurs on two-lane highway, 0 otherwise)	0.264	0.441	0.246	0.431	0.281	0.450	0.296	0.457	0.278	0.448	0.270	0.444	0.265	0.442
Four-lane indicator (1 if a crash occurs on four-lane highway, 0 otherwise)	0.595	0.491	0.606	0.489	0.577	0.494	0.588	0.492	0.595	0.491	0.604	0.489	0.607	0.489
Construction indicator (1 if a crash occurs on road under construction, 0 otherwise)	0.034	0.182	0.018	0.132	0.027	0.163	0.017	0.128	0.022	0.145	0.017	0.129	0.029	0.168
Pavement indicator (1 if pavement type is asphalt, 0 concrete)	0.923	0.267	0.926	0.262	0.921	0.270	0.928	0.258	0.929	0.257	0.928	0.259	0.928	0.259
Curve indicator (1 if a crash occurs on curve road, 0 otherwise)	0.285	0.452	0.286	0.452	0.287	0.453	0.298	0.458	0.305	0.461	0.302	0.459	0.284	0.451
Grade indicator (1 if a crash occurs on graded road, 0 otherwise)	0.102	0.303	0.101	0.301	0.116	0.320	0.099	0.299	0.109	0.311	0.100	0.300	0.097	0.296
Intersection indicator (1 if a crash occurs within intersection, 0 otherwise)	0.070	0.255	0.072	0.258	0.066	0.248	0.071	0.257	0.066	0.248	0.066	0.249	0.065	0.247

Table 2.2 Descriptive statistic of the variable used in the estimations (Cont.)

Variables	2011		2012		2013		2014		2015		2016		2017	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
U-turn indicator (1 if a crash occurs within U-turn, 0 otherwise)	0.114	0.318	0.095	0.293	0.094	0.292	0.073	0.260	0.077	0.266	0.083	0.276	0.086	0.281
Vehicle Characteristics														
Van indicator (1 if a vehicle is van, 0 otherwise)	0.028	0.165	0.022	0.146	0.016	0.124	0.025	0.155	0.022	0.147	0.027	0.161	0.022	0.145
Passenger car indicator (1 if a vehicle is passenger car, 0 otherwise)	0.350	0.477	0.344	0.475	0.350	0.477	0.365	0.481	0.328	0.470	0.350	0.477	0.356	0.479
Pick-up truck indicator (1 if a vehicle is pick-up truck, 0 otherwise)	0.449	0.498	0.473	0.499	0.480	0.500	0.468	0.499	0.483	0.500	0.454	0.498	0.467	0.499
Truck indicator (1 if a vehicle is truck, 0 otherwise)	0.155	0.362	0.143	0.350	0.130	0.337	0.131	0.338	0.142	0.349	0.152	0.359	0.133	0.340
Crash Characteristics														
OOS indicator (1 if a vehicle runs off road on straight, 0 otherwise)	0.124	0.330	0.118	0.322	0.150	0.358	0.148	0.355	0.147	0.354	0.116	0.320	0.151	0.358
OOSG indicator (1 if a vehicle runs off road on straight and hits guardrail, 0 otherwise)	0.323	0.468	0.322	0.467	0.324	0.468	0.306	0.461	0.328	0.470	0.314	0.464	0.350	0.477
MTI indicator (1 if a vehicle mounts traffic island, 0 otherwise)	0.256	0.437	0.273	0.446	0.241	0.428	0.226	0.418	0.204	0.403	0.261	0.439	0.214	0.410
OOC indicator (1 if a vehicle runs off road on curve, 0 otherwise)	0.056	0.229	0.064	0.244	0.059	0.235	0.071	0.257	0.065	0.247	0.055	0.229	0.058	0.234
OOCG indicator (1 if a vehicle runs off road on curve and hits guardrail, 0 otherwise)	0.185	0.388	0.180	0.385	0.185	0.389	0.197	0.398	0.210	0.408	0.215	0.411	0.197	0.398
Environmental and temporal Characteristics														
Surface indicator (1 if road surface is wet, 0 otherwise)	0.218	0.413	0.180	0.384	0.201	0.401	0.162	0.369	0.215	0.411	0.218	0.413	0.203	0.402
Weather indicator (1 if a crash occurs during a rain, 0 otherwise)	0.225	0.418	0.188	0.391	0.224	0.417	0.178	0.383	0.227	0.419	0.226	0.418	0.216	0.412
No-light indicator (1 if a crash occurs during nighttime without light, 0 otherwise)	0.126	0.332	0.128	0.334	0.142	0.349	0.114	0.318	0.111	0.314	0.093	0.290	0.087	0.282
With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)	0.354	0.478	0.330	0.470	0.342	0.475	0.362	0.481	0.366	0.482	0.375	0.484	0.373	0.484
Day indicator (1 if a crash occurs on weekend, 0 otherwise)	0.329	0.470	0.299	0.458	0.299	0.458	0.320	0.467	0.297	0.457	0.277	0.448	0.317	0.465
Morning indicator (1 if a crash occurs during morning peak hour 7–9:30, 0 otherwise)	0.071	0.258	0.076	0.266	0.073	0.260	0.069	0.254	0.083	0.276	0.075	0.263	0.081	0.273
Evening indicator (1 if a crash occurs during evening peak hour 16–19:30, 0 otherwise)	0.127	0.333	0.119	0.324	0.101	0.302	0.134	0.341	0.131	0.338	0.107	0.310	0.127	0.333
Spatial characteristics														
Central indicator (1 if a crash occurs in central part of country, 0 otherwise)	0.190	0.393	0.194	0.396	0.196	0.397	0.194	0.396	0.182	0.386	0.193	0.395	0.206	0.405
Eastern indicator (1 if a crash occurs in eastern part of country, 0 otherwise)	0.072	0.259	0.094	0.292	0.076	0.266	0.076	0.264	0.081	0.272	0.081	0.273	0.070	0.255
Northern indicator (1 if a crash occurs in northern part of country, 0 otherwise)	0.383	0.486	0.381	0.486	0.394	0.489	0.412	0.492	0.417	0.493	0.397	0.490	0.414	0.493
Southern indicator (1 if a crash occurs in southern part of country, 0 otherwise)	0.275	0.447	0.253	0.435	0.253	0.435	0.240	0.427	0.251	0.433	0.248	0.432	0.239	0.427

Table 2.3 Likelihood ratio test result among the selected seven-time period based on random parameter model with heterogeneity in mean (degree of freedom in parenthesis and confidence level in brackets)

	m2						
m1	2011	2012	2013	2014	2015	2016	2017
2011	-	79.00(13) [99.99%]	65.56(18) [99.99%]	51.78(15) [99.99%]	52.12(19) [99.99%]	69.82(9) [99.99%]	41.46(29) [95.13%]
2012	70.12(17) [99.99%]	-	58.20(18) [99.99%]	54.20(15) [99.99%]	58.22(19) [99.99%]	82.88(9) [99.99%]	33.00(29) [76.45%]
2013	96.48(17) [99.99%]	130.38(13) [99.99%]	-	93.54(15) [99.99%]	69.88(19) [99.99%]	101.18(9) [99.99%]	75.90(29) [99.99%]
2014	77.47(17) [99.99%]	126.31(13) [99.99%]	86.01(18) [99.99%]	-	84.01(19) [99.99%]	82.57(9) [99.99%]	40.33(29) [93.82%]
2015	97.54(17) [99.99%]	91.32(13) [99.99%]	61.50(18) [99.99%]	113.34(15) [99.99%]	-	101.1(9) [99.99%]	47.00(29) [98.63%]
2016	48.44(17) [99.99%]	63.36(13) [99.99%]	39.34(18) [99.74%]	49.60(15) [99.99%]	36.38(19) [99.99%]	-	29.98(29) [48.06%]
2017	49.66(17) [99.99%]	92.82(13) [99.99%]	50.88(18) [99.99%]	51.08(15) [99.99%]	54.52(19) [99.99%]	69.34(9) [99.99%]	-

variables on driver-injury severities between the two time periods are the same) can be rejected with more than 99% confidence level. For the transferability test using Eq. (2.10), the model estimate gives X^2 of 408.37 which is χ^2 distributed with 23 degree of freedom (number of parameters found to be statistically significant using all dataset from 2011-2017). The χ^2 value indicates that the null hypothesis (i.e., parameters over seven years [2011–2017] remain the same) can be rejected with more than 99.99% confidence level. The two series of tests provide clear evidence that the model for injury severities among drivers engaged in single-vehicle crashes developed using data from Thailand are temporally unstable.

2.6 Model Estimation Results

Figure 1 illustrates the percent distribution of the no/minor and severe/fatal injury of driver involving in single vehicle crash over the seven-years analysis period (2011-2017), which show that there is not much variation in the aggregate injury severities totals over time. However, from the recent study (Islam and Mannering, 2020), the crash injury severities models still exhibited statistically significant temporal instability over the three years considered in spite of small variation, therefore models estimations were proceeded. **Tables 2.4 to 2.10** present the model estimation results for the years 2011 to 2017, respectively. **Table 2.11** summarizes the corresponding marginal effects of significant explanatory variables for all year models for a temporal comparison. The estimated models for 2012 to 2017 displayed ρ^2 values of 0.0936, 0.0916, 0.1049, 0.0977, 0.0884, 0.1012, and 0.0702 respectively. Despite the slightly low values, previous studies considered them acceptable using the random parameters model with heterogeneity in means and variances (Alnawmasi and Mannering, 2019).

As shown in **Table 2.4 to 2.10**, a wide range of factors were found to be significant factors in determining level of driver-injury severities. It is worth mentioning that minority of those factors (median types indicator, intersection indicator, pavement type indicator) are relatively low significance (at 0.10 level); however, they are considered intuitively important to be retained in the model (Al-Bdairi et al., 2020; Kockelman and Kweon, 2002). The estimation for the 2013 to 2017 models resulted in random parameters with heterogeneity in means only, whereas two models, namely, 2011 and 2012, produced random parameters with heterogeneity in means and variance. Additionally, two models, namely, 2012 and 2014, produced statistically significant correlation coefficients among random parameters.

With regard to the comparison between the three methodological approaches, the random parameters model with heterogeneity in means and variance is statistically superior over the others in terms of capturing the unobserved heterogeneity in the 2012 model (but not in the 2011 model; **Tables 2.4 and 2.5**; the chi-square distributed likelihood ratio test with two degrees of freedom indicated a statistically significant improvement in the overall model fit at α less than 0.05). This finding maybe due to its capability of capturing an additional layer of unobserved heterogeneity (i.e., a significant factor influencing the variance of a random parameter). Considering the model estimations for 2012 and 2014, the difference between the log-likelihood at convergence for uncorrelated and correlated random parameters with heterogeneity in means was considered negligible (i.e., -668.68 vs -667.60, respectively in 2012 model; 866.98 vs -866.22, respectively in 2014 model). Additionally, the improvement in the

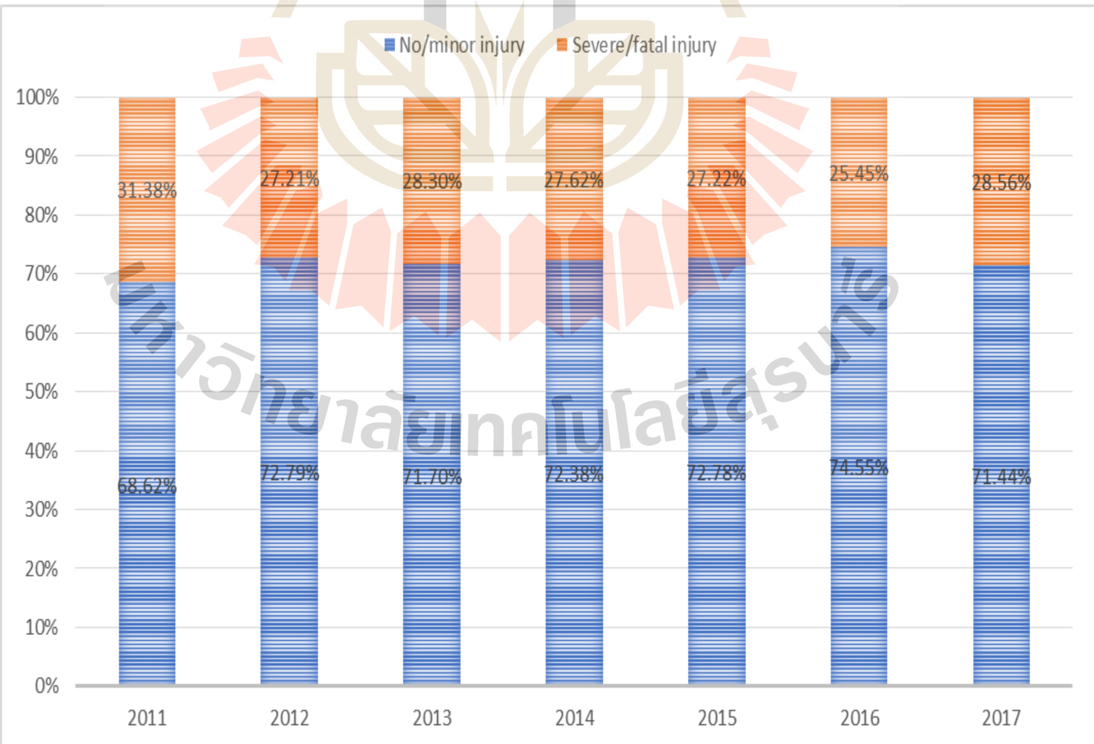

Figure 2.1 Driver-injury severities involving in single-vehicle crashes over the Years: 2011–2017

Table 2.4 Model estimation results for 2011 single-vehicle driver-injury severities on Thailand Highways

Variable	Parameter estimate	t-stat	Marginal effect
Constant	2.032	2.75	
Random Parameter			
Gender indicator (1 if a driver is male, 0 female)	-0.572	-1.05	-0.08731
Standard deviation	6.052	12.08	
Driver Characteristics			
Speed indicator (1 if a driver exceeds speed limit, 0 otherwise)	-0.509	-1.91	-0.07591
Roadway Characteristics			
Barrier median indicator (1 if a crash occurs on barrier median road, 0 otherwise)	0.919	2.33	0.15239
Pavement indicator (1 if pavement type is asphalt, 0 concrete)	-0.802	-2.74	-0.12876
Intersection indicator (1 if a crash occurs within intersection, 0 otherwise)	-0.661	-1.73	-0.07972
Vehicle Characteristics			
Passenger car indicator (1 if a vehicle is passenger car, 0 otherwise)	-1.616	-2.70	-0.20002
Pick-up truck indicator (1 if a vehicle is pick-up truck, 0 otherwise)	-1.403	-2.37	-0.19170
Truck indicator (1 if a vehicle is truck, 0 otherwise)	-2.163	-3.44	-0.20968
Crash Characteristics			
OOS indicator (1 if a vehicle runs off road on straight, 0 otherwise)	1.162	3.55	0.20187

Table 2.4 Model estimation results for 2011 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Parameter estimate	t-stat	Marginal effect
OOSG indicator (1 if a vehicle runs off road on straight and hits guardrail, 0 otherwise)	-0.973	-3.16	-0.12601
MTI indicator (1 if a vehicle mounts traffic island, 0 otherwise)	-0.801	-2.45	-0.10243
Heterogeneity in the means			
Gender indicator : Painted median indicator (1 if a crash occurs on painted median road, 0 otherwise)	-1.623	-1.98	
Gender indicator : Depressed median indicator (1 if a crash occurs on depressed median road, 0 otherwise)	-0.767	-2.55	
Gender indicator : Four-lane indicator (1 if a crash occurs on four-lane highway, 0 otherwise)	-0.738	-2.84	
Gender indicator : Van indicator (1 if a vehicle is van, 0 otherwise)	-2.334	-2.98	
Gender indicator : Morning indicator (1 if a crash occurs during morning peak hour 7–9:30, 0 otherwise)	1.784	3.60	
Gender indicator : With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)	0.734	2.84	
Heterogeneity in the variance			
Gender indicator : Two-lane indicator (1 if a crash occurs on two-lane highway, 0 otherwise)	-1.071	-7.90	

Table 2.4 Model estimation results for 2011 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Parameter estimate	t-stat	Marginal effect
Model statistic			
Number of observations	1077		
Log-likelihood at zero, $LL(0)$	-670.04		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-607.3		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.0936		

overall model fit of the correlated random parameters model compared with that of the uncorrelated model is not statistically significant indicated by the chi-square distributed likelihood ratio test. This result is consistent with that of Ahmed et al. (2021).

2.6.1 Driver characteristics

Driver characteristics (**Table 2.11**) indicate differences among the significant explanatory variables associated with injury severity levels and varied marginal effects of the risk factors of driver-injury severity over time. Regarding age group factors, drivers under 26 years were the statistically significant group for 2015 and 2017. Drivers over 50 years were significant only for 2015. Conversely, male drivers were significant only for 2017. These indicators generated positive marginal effects, which makes severe/fatal injury more likely. Regarding safety equipment, restrained drivers produced a stable effect across time (non-significant only for 2011 and 2014) with a slight variation in marginal effects. This result suggested that drivers who use seatbelts are more likely to sustain no/minor injuries. As the indicators demonstrate in **Table 2.11**, driving under the influence is a significant risk factor for the 2012, 2014, and 2017 models, making severe/fatal injury more likely. Lastly, the indicators drivers exceeding the speed limit and fatigued drivers obtained high probabilities of severe and fatal injury only for the 2017 model. Behnood and Mannering (2015) produced a similar finding on fatigued drivers, explaining that police officers could have changed reporting practices and frequently identified the cause of severe crashes as fatigue in drivers (In Thailand, road safety and accident investigation experts (under DOH), provides road safety campaign annually targeting improvement of accident recording practice by police officers, therefore, this could also be the reason of the changes in reporting behavior of the officer over time).

2.6.2 Roadway characteristics

Table 2.11 shows that roadway characteristics also played an important role over time. First, three median types were found significant across several times. For example, crashes on the raised median road were statistically significant for the 2015, 2016, and 2017 models, whereas crashes on the depressed median road were significant for the 2012, 2016, and 2017 models. The two indicators produced stable effects with notable variations in marginal effects (remained positive across time), making severe/fatal injury more likely. Similarly, crashes occurring on barrier median roads generated stable effects across time (i.e., 2011, 2013, 2015, 2016, and 2017) with significant increases in marginal effects for 2016 and 2017. This finding evinced a high probability of severe/fatal injury. Generally, barrier median and raised median are found in urban roadways, where traffic capacity is high and requires a lower speed limit. Stable increases in the marginal effects of severe/fatal injuries may be due to the high-impact crashes generated by high-speed driving (This notion is unclear; however, it is an interesting avenue for future research by empirically exploring factors influencing driver-injury severity in crashes related to excessive speed.). This finding is also in line with that of Khorashadi et al. (2005).

Crashes on asphalt pavement significantly affected driver-injury severities for five periods, namely, 2011 and from 2014 to 2017 (**Table 2.11**), which displayed increased probabilities of no/minor injury severities. However, the effect shifted to a high probability of severe/fatal injury for 2017 (the underlying reason is unclear; an additional investigation is required to confirm the pattern; that is, if it stays unstable in years later than 2017). Crashes on graded roads were significant factors in the 2013 and 2017 models, which increased the probabilities of severe/fatal injuries. Finally, the marginal effect of crashes occurring within intersections (2011 and 2017 models: **Table 2.11**) and U-turns (2014 and 2017 models; **Table 2.11**) was also statistically significant and produced high probabilities of no/minor injury.

Table 2.5 Model estimation results for 2012 single-vehicle driver-injury severities on Thailand Highways

Variable	Correlated random parameters with heterogeneity in means			Random parameters with heterogeneity in means and variances		
	Parameter estimate	t-stat	Marginal effect	Parameter estimate	t-stat	Marginal effect
Constant	0.352	1.02		0.517	1.32	
Random Parameter						
With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)	-0.396	-0.45	-0.08142	-2.583	-2.11	-0.35586
Standard deviation	2.169	10.07		2.599	8.35	
Day indicator (1 if a crash occurs on weekend, 0 otherwise)	0.741	0.94	0.16320	1.184	1.32	0.24448
Standard deviation	0.278	1.99		0.165	1.72	
Driver Characteristics						
Restrain indicator (1 if a driver uses seatbelt, 0 otherwise)	-0.181	-1.65	-0.03776	-0.241	-2.03	-0.03901
DUI indicator (1 if a driver is under influence of alcohol, 0 otherwise)	1.469	3.26	0.33107	1.469	3.13	0.26142

Table 2.5 Model estimation results for 2012 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Correlated random parameters with heterogeneity in means			Random parameters with heterogeneity in means and variances		
	Parameter estimate	t-stat	Marginal effect	Parameter estimate	t-stat	Marginal effect
Depressed median indicator (1 if a crash occurs on depressed median road, 0 otherwise)	-	-	-	0.234	1.81	0.04164
Vehicle Characteristics						
Passenger car indicator (1 if a vehicle is passenger car, 0 otherwise)	-0.834	-2.41	-0.16477	-1.061	-2.80	-0.16119
Pick-up truck indicator (1 if a vehicle is pick-up truck, 0 otherwise)	-0.734	-2.14	-0.14951	-0.925	-2.46	-0.14645
Truck indicator (1 if a vehicle is truck, 0 otherwise)	-0.854	-2.34	-0.15798	-0.978	-2.43	-0.13960
Crash Characteristics						
OOSG indicator (1 if a vehicle runs off road on straight and hits guardrail, 0 otherwise)	-0.601	-4.50	-0.12165	-0.507	-3.41	-0.08056
MTI indicator (1 if a vehicle mounts traffic island, 0 otherwise)	-0.719	-4.85	-0.14321	-0.703	-4.41	-0.10944

Table 2.5 Model estimation results for 2012 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Correlated random parameters with heterogeneity in means			Random parameters with heterogeneity in means and variances		
	Parameter estimate	t-stat	Marginal effect	Parameter estimate	t-stat	Marginal effect
Heterogeneity in means						
With-light indicator : Old-driver indicator (1 if a driver is aged 50 years and above, 0 otherwise)	0.605	2.10		0.729	2.08	
With-light indicator : Young-driver indicator (1 if a driver is aged below 26, 0 otherwise)	1.358	3.71		1.816	4.08	
Day indicator : Young-driver indicator (1 if a driver is aged below 26, 0 otherwise)	-1.037	-2.37		-1.057	-2.13	
Heterogeneity in variance						
With-light indicator : OOS indicator (1 if a vehicle runs off road on straight, 0 otherwise)				6.381	5.89	
Model statistic						
Number of observations	1242			1242		

Table 2.5 Model estimation results for 2012 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Correlated random parameters with heterogeneity in means			Random parameters with heterogeneity in means and variances		
	Parameter estimate	t-stat	Marginal effect	Parameter estimate	t-stat	Marginal effect
Log-likelihood at zero, $LL(0)$	-727.04			-727.04		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-667.60			-660.41		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.0818			0.0916		
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters with heterogeneity in means model						
	With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)			Day indicator (1 if a crash occurs on weekend, 0 otherwise)		
With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)	2.169(10.07)[1.0000]			1.250(7.19)[0.9998]		
Day indicator (1 if a crash occurs on weekend, 0 otherwise)	1.250(7.19)[0.9998]			0.278(1.99)[1.0000]		

2.6.3 Vehicle characteristics

The marginal effects of the vehicle type (except for vans) had similar effects and trends (**Table 2.11**). For 2011, 2012, 2014, and 2017 crashes involving passenger cars, pick-up trucks, and trucks produced negative marginal effects, implying that no/minor injury is more likely. This result is consistent with that of Yu et al. (2020; 2021). This temporal stability and variability may be due to the constant improvement of vehicle safety features and drivers' adaptations to them (Behnood and Mannering, 2015). Interestingly, for 2017, crashes involving vans exhibit a high probability of severe/fatal injury (In Thailand, this may be due the old vans or minibus vehicle which in general the safety device in the vehicle mostly lacks off the airbag protection (majority do not have airbag) and low-quality safety feature (such as seatbelt, braking system, etc.)).

2.6.4 Crash characteristics

The result demonstrated that all indicator variables in this group influenced driver injury severities for several years. For example, vehicles running off a straight road was a statistically significant factor for the 2011, 2014, 2016, and 2017 models, whereas vehicles running off the road and hitting guardrails were significant for the 2011, 2012, 2013, 2015, and 2017 models. In addition, crashes involving vehicles running off roads on curved roads were significant for 2017. Vehicles running off curved roads and hitting guardrails were statistically significant parameters for determining driver-injury severities for 2013 and 2015. These findings were intuitive. When a vehicle runs off a straight or curved road, the probability of severe/fatal injury increases. However, if a vehicle hits the guardrail on the side of the road, then the probability of severe and fatal injury is less likely. The result indicates the essential function of roadside safety through installed guardrails. This finding is consistent with previous studies' findings (Anarkooli et al., 2017; Roque et al., 2015; Se et al., 2020b, 2020c).

2.6.5 Environmental and temporal attribute

For 2015 (**Table 2.11**), crashes occurring during morning peak hours (7:00–9:30 AM) had a higher likelihood of severe/fatal injury. In 2017 model, the indicators crashes occurring during rain and at night on lighted roads decreased the probability of severe and fatal injury; however, crashes occurring on weekends increased the probability of severe and fatal injury.

Table 2.6 Model estimation results for 2013 single-vehicle driver-injury severities on Thailand Highways

Variable	Parameter estimate	t-stat	Marginal effect
Constant	-0.937	-1.57	
Random Parameter			
No-light indicator (1 if a crash occurs during nighttime without light, 0 otherwise)	-5.748	-2.36	-0.20706
Standard deviation	5.675	5.60	
Driver Characteristics			
Restrain indicator (1 if a driver uses seatbelt, 0 otherwise)	-0.248	-2.21	-0.03169
Roadway Characteristics			
Barrier median indicator (1 if a crash occurs on barrier median road, 0 otherwise)	0.763	2.64	0.11553
Curve indicator (1 if a crash occurs on curve road, 0 otherwise)	-0.622	-2.13	-0.07471
Grade indicator (1 if a crash occurs on graded road, 0 otherwise)	0.466	2.42	0.06557
Crash Characteristics			
OOSG indicator (1 if a vehicle runs off road on straight and hits guardrail, 0 otherwise)	-0.806	-3.11	-0.09721
MTI indicator (1 if a vehicle mounts traffic island, 0 otherwise)	-0.832	-3.15	-0.09686
OOCG indicator (1 if a vehicle runs off road on curve and hits guardrail, 0 otherwise)	-0.712	-2.10	-0.08152

Table 2.6 Model estimation results for 2013 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Parameter estimate	t-stat	Marginal effect
Spatial characteristics			
Central indicator (1 if a crash occurs in central part of country, 0 otherwise)	0.607	2.48	0.08545
Eastern indicator (1 if a crash occurs in eastern part of country, 0 otherwise)	0.561	1.93	0.08075
Northern indicator (1 if a crash occurs in northern part of country, 0 otherwise)	0.401	1.72	0.05290
Heterogeneity in the means			
No-light indicator: Depressed median indicator (1 if a crash occurs on depressed median road, 0 otherwise)	1.354	2.08	
No-light indicator: Intersection indicator (1 if a crash occurs within intersection, 0 otherwise)	2.895	2.59	
No-light indicator: U-turn indicator (1 if a crash occurs within U-turn, 0 otherwise)	2.160	2.16	
No-light indicator: Surface indicator (1 if road surface is wet, 0 otherwise)	-3.641	-2.80	
No-light indicator: Two-lane indicator (1 if a crash occurs on two-lane highway, 0 otherwise)	2.395	2.33	

Table 2.6 Model estimation results for 2013 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Parameter estimate	t-stat	Marginal effect
No-light indicator: Four-lane indicator (1 if a crash occurs on four-lane highway, 0 otherwise)	2.186	2.28	
No-light indicator: Gender indicator (1 if male driver, 0 female driver)	-2.545	-3.08	
Model statistic			
Number of observations	1350		
Log-likelihood at zero, $LL(0)$	-804.24		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-719.83		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.1049		

Table 2.7 Model estimation results for 2014 single-vehicle driver-injury severities on Thailand Highways

Variable	Parameter estimate	t-stat	Marginal effect
Constant	0.241	0.59	
Random Parameter			
With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)	-0.531	-1.00	-0.08376
Standard deviation	2.045	11.38	
Day indicator (1 if a crash occurs on weekend, 0 otherwise)	-1.103	-1.50	-0.16248
Standard deviation	1.571	9.29	
Driver Characteristics			
DUI indicator (1 if a driver is under influence of alcohol, 0 otherwise)	1.622	4.27	0.33071
Roadway Characteristics			

Table *2.7* Model estimation results for 2014 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Parameter estimate	t-stat	Marginal effect
Pavement indicator (1 if pavement type is asphalt, 0 concrete)	-0.445	-2.30	-0.07869
U-turn indicator (1 if a crash occurs within U-turn, 0 otherwise)	-0.515	-2.25	-0.07575
Vehicle Characteristics			
Passenger car indicator (1 if a vehicle is passenger car, 0 otherwise)	-0.782	-2.15	-0.12048
Pick-up truck indicator (1 if a vehicle is pick-up truck, 0 otherwise)	-0.849	-2.35	-0.13587
Truck indicator (1 if a vehicle is truck, 0 otherwise)	-0.926	-2.43	-0.12795
Crash Characteristics			
OOS indicator (1 if a vehicle runs off road on straight, 0 otherwise)	1.158	7.95	0.22446
Spatial characteristics			
Eastern indicator (1 if a crash occurs in eastern part of country, 0 otherwise)	0.380	2.11	0.06715
Heterogeneity in means			
With-light indicator : Old-driver indicator (1 if a driver is aged 50 years and above, 0 otherwise)	-0.614	-1.95	
With-light indicator : Painted median indicator (1 if a crash occurs on painted median road, 0 otherwise)	-0.928	-1.96	
With-light indicator : Surface indicator (1 if road surface is wet, 0 otherwise)	-1.131	-1.94	

Table *2.7* Model estimation results for 2014 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Parameter estimate	t-stat	Marginal effect
Day indicator : Gender indicator (1 if male driver, 0 female driver)	0.870	2.20	
Day indicator : Intersection indicator (1 if a crash occurs within intersection, 0 otherwise)	-0.856	-1.73	
Model statistic			
Number of estimated parameters	40		
Number of observations	1629		
Log-likelihood at zero, $LL(0)$	-960.084		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-866.228		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.0977		

Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters with heterogeneity in means model

	With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)	Day indicator (1 if a crash occurs on weekend, 0 otherwise)
With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)	2.045(11.38)[1.0000]	-1.090(-7.08)[-0.5701]
Day indicator (1 if a crash occurs on weekend, 0 otherwise)	-1.090(-7.08)[-0.5701]	1.571(9.29)[1.0000]

Table 2.8 Model estimation results for 2015 single-vehicle driver-injury severities on Thailand Highways

Variable	Parameter estimate	t-stat	Marginal effect
Constant	-0.359	-0.82	
Random Parameter			
Day indicator (1 if a crash occurs on weekend, 0 otherwise)	-0.6602	-3.72	-0.11516
Standard deviation	3.020	10.77	
Driver Characteristics			
Young-driver indicator (1 if a driver is aged below 26, 0 otherwise)	0.241	1.68	0.04636
Old-driver indicator (1 if a driver is aged 50 years and above, 0 otherwise)	0.218	2.03	0.04148
Restrain indicator (1 if a driver uses seatbelt, 0 otherwise)	-0.326	-3.35	-0.05992
Roadway Characteristics			
Raised median indicator (1 if a crash occurs on raised median road, 0 otherwise)	0.258	2.01	0.04906
Barrier median indicator (1 if a crash occurs on barrier median road, 0 otherwise)	0.342	1.80	0.06703
Pavement indicator (1 if pavement type is asphalt, 0 concrete)	-0.317	-1.83	-0.06172
Vehicle Characteristics			
Pick-up truck indicator (1 if a vehicle is pick-up truck, 0 otherwise)	-0.468	-1.84	-0.08630
OOSG indicator (1 if a vehicle runs off road on straight and hits guardrail, 0 otherwise)	-0.890	-6.77	-0.15582
MTI indicator (1 if a vehicle mounts traffic island, 0 otherwise)	-1.035	-6.58	-0.16853

Table 2.8 Model estimation results for 2015 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Parameter estimate	t-stat	Marginal effect
OOCG indicator (1 if a vehicle runs off road on curve and hits guardrail, 0 otherwise)	-0.893	-5.12	-0.14823
Environmental and temporal Characteristics			
Morning indicator (1 if a crash occurs during morning peak hour 7–9:30, 0 otherwise)	0.330	2.03	0.06434
Spatial characteristics			
Central indicator (1 if a crash occurs in central part of country, 0 otherwise)	0.457	1.99	0.08878
Eastern indicator (1 if a crash occurs in eastern part of country, 0 otherwise)	0.519	1.97	0.10304
Northern indicator (1 if a crash occurs in northern part of country, 0 otherwise)	0.474	2.21	0.08878
Southern indicator (1 if a crash occurs in southern part of country, 0 otherwise)	0.816	3.77	0.16146
Heterogeneity in means			
Day indicator : Construction indicator (1 if a crash occurs on road under construction, 0 otherwise)	1.793	2.57	
Day indicator : OOS indicator (1 if a vehicle runs off road on straight, 0 otherwise)	0.711	2.27	
Model statistic			
Number of observations	1712		
Log-likelihood at zero, $LL(0)$	-1002.25		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-913.62		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.0884		

Table 2.9 Model estimation results for 2016 single-vehicle driver-injury severities on Thailand Highways

Variable	Parameter estimate	t-stat	Margin effect
Random Parameter			
Gender indicator (1 if male driver, 0 female driver)	0.213	0.62	0.04556
Standard deviation	0.147	1.68	
Driver Characteristics			
Restrain indicator (1 if a driver uses seatbelt, 0 otherwise)	-0.323	-2.29	-0.07019
Roadway Characteristics			
Raised median indicator (1 if a crash occurs on raised median road, 0 otherwise)	0.582	3.04	0.13084
Depressed median indicator (1 if a crash occurs on depressed median road, 0 otherwise)	0.478	2.57	0.10465
Barrier median indicator (1 if a crash occurs on barrier median road, 0 otherwise)	0.658	2.48	0.15059
Pavement indicator (1 if pavement type is asphalt, 0 concrete)	-0.486	-1.99	-0.11061
Crash Characteristics			
OOS indicator (1 if a vehicle runs off road on straight, 0 otherwise)	0.631	2.14	0.14569
Heterogeneity in means			
Gender indicator: Morning indicator (1 if a crash occurs during morning peak hour 7–9:30, 0 otherwise)	0.429	1.66	
Model statistic			
Number of observations	829		
Log-likelihood at zero, $LL(0)$	-470.25		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-422.67		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.1012		

Table 2.10 Model estimation results for 2017 single-vehicle driver-injury severities on Thailand Highways

Variable	Parameter estimate	t-stat	Margin effect
Random Parameter			
Constant	-12.87	-6.63	
Standard deviation	18.154	10.04	
MTI indicator (1 if a vehicle mounts traffic island, 0 otherwise)	-13.998	-7.96	-0.10505
Standard deviation	39.82	9.56	
Driver Characteristics			
Young-driver indicator (1 if a driver is aged below 26, 0 otherwise)	0.693	2.05	0.01707
Gender indicator (1 if male driver, 0 female driver)	1.412	3.11	0.03203
Restrain indicator (1 if a driver uses seatbelt, 0 otherwise)	-0.819	-2.94	-0.01958
DUI indicator (1 if a driver is under influence of alcohol, 0 otherwise)	4.470	4.23	0.12272
Speed indicator (1 if a driver exceeds speed limit, 0 otherwise)	2.345	4.53	0.05184
Fatigue indicator (1 if a driver falls asleep, 0 otherwise)	3.681	5.52	0.10021
Roadway Characteristics			
Raised median indicator (1 if a crash occurs on raised median road, 0 otherwise)	2.811	6.04	0.06990
Depressed median indicator (1 if a crash occurs on depressed median road, 0 otherwise)	2.135	5.31	0.05387
Barrier median indicator (1 if a crash occurs on barrier median road, 0 otherwise)	5.865	7.27	0.16470

Table 2.10 Model estimation results for 2017 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Parameter estimate	t-stat	Margin effect
Construction indicator (1 if a crash occurs on road under construction, 0 otherwise)	1.739	2.37	0.04420
Pavement indicator (1 if pavement type is asphalt, 0 concrete)	1.743	3.02	0.03910
Grade indicator (1 if a crash occurs on graded road, 0 otherwise)	2.012	4.09	0.04881
Intersection indicator (1 if a crash occurs within intersection, 0 otherwise)	-3.496	-4.83	-0.06873
U-turn indicator (1 if a crash occurs within U-turn, 0 otherwise)	-4.291	-5.86	-0.07867
Vehicle Characteristics			
Van indicator (1 if a vehicle is van, 0 otherwise)	1.875	1.65	0.04667
Passenger car indicator (1 if a vehicle is passenger car, 0 otherwise)	-3.931	-3.67	-0.06946
Pick-up truck indicator (1 if a vehicle is pick-up truck, 0 otherwise)	-2.246	-4.54	-0.08222
Truck indicator (1 if a vehicle is truck, 0 otherwise)	-3.688	-4.09	-0.07788
Crash Characteristics			
OOS indicator (1 if a vehicle runs off road on straight, 0 otherwise)	9.073	7.67	0.37456
OOSG indicator (1 if a vehicle runs off road on straight and hits guardrail, 0 otherwise)	-1.480	-1.94	-0.03456
OOC indicator (1 if a vehicle runs off road on curve, 0 otherwise)	5.679	4.88	0.15027
Environmental and temporal Characteristics			

Table 2.10 Model estimation results for 2017 single-vehicle driver-injury severities on Thailand Highways (Cont.)

Variable	Parameter estimate	t-stat	Margin effect
Weather indicator (1 if a crash occurs during a rain, 0 otherwise)	-2.329	-2.68	-0.05543
With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)	-2.046	-5.73	-0.04919
Day indicator (1 if a crash occurs on weekend, 0 otherwise)	0.679	2.40	0.01661
Spatial characteristics			
Central indicator (1 if a crash occurs in central part of country, 0 otherwise)	2.261	3.64	0.05721
Eastern indicator (1 if a crash occurs in eastern part of country, 0 otherwise)	2.069	2.80	0.05246
Southern indicator (1 if a crash occurs in southern part of country, 0 otherwise)	2.844	4.61	0.07167
Heterogeneity in means			
MTI indicator : Morning indicator (1 if a crash occurs during morning peak hour 7–9:30, 0 otherwise)	5.434	3.33	
Model statistic			
Number of observations	2038		
Log-likelihood at zero, $LL(0)$	-1219.011		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$	-1133.571		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.0702		

2.6.6 Spatial characteristics

Regarding region, three indicators for 2013 (i.e., crashes occurring in the central, eastern, and northern parts of the country), one indicator for 2014 (crashes occurring in the eastern part), all indicators for 2015, and three indicators for 2017 (crashes occurring in the central, eastern, and southern parts of the country) significantly increased the probability of severe/fatal injuries.

2.6.7 Heterogeneity in the means and variance of random parameters

The 2011 model indicated that the male drivers resulted in random parameters with significant heterogeneity in means and variance (**Table 2.4**). Crashes occurring during morning peak hours and at night on lighted roads caused an upward shift in the mean for the random parameters of the male driver indicator. This finding suggested that severe/fatal injury is more likely. However, crashes on painted and depressed median road, four-lane road, and involving van indicator cause a downward shift in the mean of male driver indicator, which translates to a high probability of no/minor injuries. For heterogeneity variance, crashes involving male drivers decreased variance among crashes occurring on two-lane highways.

Table 2.5 shows that, for the 2012 model, two indicators, namely, crashes occurring at nighttime on lighted roads and during the weekends, resulted in a random parameter. For crashes occurring at nighttime on lighted roads, crashes involving young and older drivers increased the mean, which leads to the increased probability of severe/fatal injuries. Conversely, young drivers decreased the mean of the crashes occurring during weekends, implying that no/minor injury is more likely. Moreover, crashes occurring at nighttime on lighted roads increased the variation for crashes involving vehicles running off straight roads.

Table 2.6 indicates that, for the 2013 model, crashes occurring at nighttime on unlit roads resulted in a random parameter and produced significant heterogeneity in the means. For this variable, crashes occurring on roads with depressed medians, within intersection areas, U-turn areas, and on two- and four-lane highways caused an upward shift in the mean, indicating an increased probability of severe/fatal injury. However, crashes on wet roads and involving male drivers decreased the means of the random parameter, making no/minor injury more likely.

Table 2.11 Summary of marginal effect of significant parameters from 2011-2017 (Bold values indicate random parameter)

Variable	2011	2012	2013	2014	2015	2016	2017
Driver Characteristics							
Young-driver indicator (1 if a driver is aged below 26, 0 otherwise)					0.04636		0.01707
Old-driver indicator (1 if a driver is aged 50 years and above, 0 otherwise)					0.04148		
Gender indicator (1 if male driver, 0 female driver)	**-0.08731**					**0.04556**	0.03203
Restrain indicator (1 if a driver uses seatbelt, 0 otherwise)		-0.03901	-0.03169		-0.05992	-0.07019	-0.01958
DUI indicator (1 if a driver is under influence of alcohol, 0 otherwise)		0.26142		0.33071			0.12272
Speed indicator (1 if a driver exceeds speed limit, 0 otherwise)	-0.07591						0.05184
Fatigue indicator (1 if a driver falls asleep, 0 otherwise)							0.10021
Roadway Characteristics							
Raised median indicator (1 if a crash occurs on raised median road, 0 otherwise)					0.04906	0.13084	0.06990
Depressed median indicator (1 if a crash occurs on depressed median road, 0 otherwise)		0.04164				0.10465	0.05387
Barrier median indicator (1 if a crash occurs on barrier median road, 0 otherwise)	0.15239		0.11553		0.06703	0.15059	0.16470
Construction indicator (1 if a crash occurs on road under construction, 0 otherwise)							0.04420
Pavement indicator (1 if pavement type is asphalt, 0 concrete)	-0.12876			-0.07869	-0.06172	-0.11061	0.03910
Curve indicator (1 if a crash occurs on curve road, 0 otherwise)			-0.07471				
Grade indicator (1 if a crash occurs on graded road, 0 otherwise)			0.06557				0.04881
Intersection indicator (1 if a crash occurs within intersection, 0 otherwise)	-0.07972						-0.06873
U-turn indicator (1 if a crash occurs within U-turn, 0 otherwise)				-0.07575			-0.07867
Vehicle Characteristics							
Van indicator (1 if a vehicle is van, 0 otherwise)							0.04667
Passenger car indicator (1 if a vehicle is passenger car, 0 otherwise)	-0.20002	-0.16119		-0.12048			-0.06946

Table 2.11 Summary of marginal effect of significant parameters from 2011-2017 (Bold values indicate random parameter) (Cont.)

Variable	2011	2012	2013	2014	2015	2016	2017
Pick-up truck indicator (1 if a vehicle is pick-up truck, 0 otherwise)	-0.19170	-0.14645		-0.13587	-0.08630		-0.08222
Truck indicator (1 if a vehicle is truck, 0 otherwise)	-0.20968	-0.13960		-0.12795			-0.07788
Crash Characteristics							
OOS indicator (1 if a vehicle runs off road on straight, 0 otherwise)	0.20187			0.22446		0.14569	0.37456
OOSG indicator (1 if a vehicle runs off road on straight and hits guardrail, 0 otherwise)	-0.12601	-0.08056	-0.09721		-0.15582		-0.03456
MTI indicator (1 if a vehicle mounts traffic island, 0 otherwise)	-0.10243	-0.10944	-0.09686		-0.16853		**-0.10505**
OOC indicator (1 if a vehicle runs off road on curve, 0 otherwise)							0.15027
OOCG indicator (1 if a vehicle runs off road on curve and hits guardrail, 0 otherwise)			-0.08152		-0.14823		
Environmental and temporal Characteristics							
Weather indicator (1 if a crash occurs during a rain, 0 otherwise)							-0.05543
No-light indicator (1 if a crash occurs during nighttime without light, 0 otherwise)			**-0.20706**				
With-light indicator (1 if a crash occurs during nighttime with light, 0 otherwise)		**-0.35586**		**-0.08376**			-0.04919
Day indicator (1 if a crash occurs on weekend, 0 otherwise)		**0.24448**		**-0.16248**	**-0.11516**		0.01661
Morning indicator (1 if a crash occurs during morning peak hour 7–9:30, 0 otherwise)					0.06434		
Spatial characteristics							
Central indicator (1 if a crash occurs in central part of country, 0 otherwise)			0.08545		0.08878		0.05721
Eastern indicator (1 if a crash occurs in eastern part of country, 0 otherwise)			0.08075	0.06715	0.10304		0.05246
Northern indicator (1 if a crash occurs in northern part of country, 0 otherwise)			0.05290		0.08878		
Southern indicator (1 if a crash occurs in southern part of country, 0 otherwise)					0.16146		0.07167

Regarding the 2014 model (**Table 2.7**), crashes occurring at nighttime on lighted roads and during weekends resulted in random parameters and produced heterogeneity in the means. Crashes involving old drivers, occurring on roads with painted medians, and wet roads decreased the mean of crashes at nighttime on lighted roads, which suggested an increased probability of no/minor injury. For crashes occurring during the weekend, male drivers increased the mean, suggesting a decreased probability of no/minor injury, whereas crashes occurring within intersections decreased the mean, rendering no/minor injury more likely.

For the 2015 model (**Table 2.8**), only the indicator crashes occurring during weekends produced a random parameter with significant heterogeneity in the mean. The indicators for crashes on roads under construction and vehicles running off straight roads increased the mean of this random parameter, which increased the possibility of severe/fatal injury.

Table 2.9 demonstrates that the indicator male drivers produced a random parameter with heterogeneity in mean for the 2016 model. Crashes during morning peak hours (7:00–9:30 AM) increased the mean, making severe/fatal injury more likely.

Finally, the indicator vehicle hitting the traffic island for the 2017 model (**Table 2.10**) resulted in a random parameter with significant heterogeneity in the mean. Crashes during morning peak hours (7:00–9:30 AM) increased the mean, making severe/fatal injury more likely.

2.6.8 Insights offered by correlated random parameters

The result of the model specification with significant correlations among random parameters demonstrated that the correlation coefficient of two random parameters, namely, crashes occurring at nighttime on lighted roads and during weekends (2012 model; **Table 2.5**), was positive (coefficient = 0.9998). This finding indicated that the interaction between unobserved heterogeneity and unobserved characteristics, as captured by the two random parameters, exerted an overall positive effect on the injury severity level. This result implied that drivers involved in crashes occurring during weekends and at nighttime on lighted roads are more likely to lead to severe/fatal injuries. In contrast, the correlation coefficient of these two random parameters became negative in 2014 model (coefficient = −0.5701), which led to a decreased probability of severe/fatal injury. This result suggested that the effect of crash occurring during weekends and at nighttime on lighted streets on injury severity is temporally unstable. Once again, this result is intuitive: crashes occurring during weekends and at nighttime correlated significantly, because drunk and drowsy drivers are more likely to drive at night and during weekends (non-working days). This temporal instability may be due to various campaign efforts for safety education and the reinforcement of the law on drunk driving (For example, in Thailand, Road Traffic Act (No.10) BE 2557 (2014), Section 43 (2), indicate that traffic officer has the authority to stop the vehicle and test whether driver is driving while being drunk, and if driver reject testing to measure the alcohol content, driver is assumed to be “driving while drunk”, therefore plead guilty and will be prosecuted according to the law).

2.7 Conclusions

Without a doubt, single-vehicle crashes remain the major concern for roadway users and highway administrators. Despite the efforts of previous studies on single-vehicle injury severities to investigate the temporal stability of factors that influenced single-vehicle crashes, such studies employed data from developed countries, such as the USA. To address this research gap, the current study used data from a developing country, namely, Thailand from 2011 to 2017. Moreover, it provided an in-depth investigation of the temporal stability of factors that influence driver-injury severities using the random parameters model allowing possible heterogeneity in the means and variances approach and the correlated random parameters model with heterogeneity in the means (empirically explore when year-model result in two or more statistically significant random parameters) for seven-year models individually. Two levels of driver-injury severities were considered, namely, no/minor injury and severe/fatal injury. The models considered a wide range of factors, such as, driver, roadway, vehicle, crash, environmental and temporal, and spatial characteristics.

Two series of likelihood ratio tests were carried out to explore the temporal stability of the determinants. The result shows that substantial temporal instability existed in the model specifications and estimated parameters across the periods under study. The magnitude of the marginal effect of each significant factor varied across time periods. Despite the non-significance of a few year-models and the variation in marginal effects, many explanatory variables (i.e., use of restraint, driving under the influence of alcohol, roads with raised, depressed, and barrier medians, vehicle type [passenger cars, pick-up trucks, and large trucks], crashes involving vehicles that run off road on straight, run off road on straight and hit a guardrail, and crashes on mounted traffic island) exhibited stable effects over time. In contrast, other factors (i.e., male drivers, exceeding the speed limit, crashes on asphalt pavement, crashes on weekends, and crashes on weekends during nighttime on a lighted road) were temporally unstable. The possible sources of observed temporal instability and variability in the study may be due to the improvements in the safety features of vehicles, driver adaptation to such changes in technology, changes in officer judgment in recording accident data, various safety education campaign efforts and reinforcement of law on drunk-driving which were thoroughly explained by and consistent with the those of Behnood and Mannering (2015), Mannering (2018) and Marcoux et al., 2018. With regard to the significant factors and temporal instability observed in the research, the said finding may be used to assist and guide decision makers in policy generation for plans to mitigate driver-injury severities.

Although the reason underlying some of the observed temporal instability and variability is unclear, the finding emphasizes the importance of the temporal instability of the factors that influence the outcomes of driver-injury severities. In other words, studies on crash severity that ignore temporal stability may lead to high levels of bias and inaccurate conclusions.

With regard to methodological approaches, the overall fit of the random parameter model with heterogeneity in mean and variance generated statistically significant improvements over the uncorrelated and correlated random parameter model with heterogeneity in means (see **Table 2.5**). As well discuss in the work of Ahmed et al., (2021), if the uncorrelated model is chosen over the correlated model, the insightful finding generated by the correlation coefficient would be ignored. On the other hand, in the same manner, heterogeneity in the variance of random parameter would be neglected (assuming there are any; despite providing the superior model fit as shown in **Table 2.5**), if correlated model is selected. To this end, future research should select the best trade-off between model fit, prediction accuracy, and explanatory power in determining the best model specification (Ahmed et al., 2021).

In the context of the direction for future research, one important aspect noted by Islam and Mannering (2020) is that the temporal instability of risk factors found in many studies could be the result of a subset of observations (i.e., exist in some part of the observations if not most of the observations). Thus, this issue could be an important one that should be considered in future studies that aim to find deep insight into temporal elements in the analysis of crash injury severity (i.e., differentiate subsets between crashes involving speeding driving and non-speeding driving, rural and urban regions, times-of-the-day, and days-of-the-week).

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CHAPTER III

ANALYSIS OF DRIVER-INJURY SEVERITY: A COMPARISON BETWEEN SPEEDING AND NON-SPEEDING DRIVING CRASH ACCOUNTING FOR TEMPORAL AND UNOBSERVED EFFECTS

3.1 Abstract

This paper aims to investigates the differences between temporal stability of factors influencing driver-injury severities in crashes involving speeding and non-speeding driving using a six-years (2012–2017) crash data in Thailand. With two possible driver injury severity outcomes (no/minor and severe/fatal), random parameter binary logit models, that allow for heterogeneity in means and variances, were estimated to fully account for unobserved heterogeneities (i.e., allow crash-level factors to vary across crashes and to influence random parameter distribution). While most factors were unstable over time, speeding crash models result showed that stable factors decreasing probability of severe/fatal injury were restraint, van, passenger car, pickup truck, running-off-road on straight and hitting guardrail and mounting traffic island; whereas stable factor increasing probability of severe/fatal injury were central/eastern/southern regions. In non-speeding driving crash model, stable factors decreasing probability of severe/fatal injury were restraint, truck, and running-off-road on straight and hitting guardrail; whereas stable factors increasing probability of severe and fatal injury were under influence of alcohol and van. The findings of this research could potentially be utilized to improve highway safety and facilitate the development of a more effective crash injury mitigation policies. Practical-related recommendation based on the results are also provided.

3.2 Introduction

Excessive and inappropriate speed are mainly responsible for high proportions of mortality and morbidity and contributes to approximately one-third of deaths on roads in high-income countries. Moreover, speeding is also estimated to be the main contributory factor in approximately half of all road crashes in several low- and middle-income developing countries (WHO, 2020). Thailand, in particular, is a middle-income and developing country that encounters tremendous economic and emotional burdens due to road accidents with 32.8 per 100,000 death rate, and Thai highways are regarded as the deadliest in Southeast Asia and among the worst in the world (WHO, 2018). In addition, between 2012 and 2017, single-vehicle crashes (highest crash rate (Champahom et al., 2020b)) involving drivers that exceed the speed limit account for approximately 77% of the total occurrences of total crashes and are responsible for more than 76% of severe and fatal injuries (this data is derived from the statistical analysis of the Highway Accident Information Management System, Department of Highways, Thailand). This inevitable situation arises from the enhanced capacity of modern cars with respect to speed and an increasing demand to build more roads with higher standards which further encourage speeding behaviour (Kanitpong et al., 2013). With responsibility for considerably high number of fatalities, there is a clear need to study influencing factors of driver-injury severity relative to their speeding behaviours.

In general, speeding-related crashes are decided when the driver involved was charged with a speeding-related offense, racing, driving too fast for conditions, or exceeding the posted speed limit (Liu and Chen, 2009; NHTSA, 2020). Speeding behaviours have been found to play an important role as a key risk factor influencing both crash likelihood and resultant injury severity (Broughton et al., 2020; Ratanavaraha and Suangka, 2014). Høye (2020) found that speeding drivers are frequently male, unbelted, unlicensed and driving old cars. However, they are less often fatigued, ill, or suicidal. Anastasopoulos and Mannering (2016) reported that several factors, such as age, gender, marital status, number of children, level of education, level of income, and pavement type, influence the choice of speed in the presence of speed limits. In addition, Council et al. (2010) found the high levels of association between several factors with proportions of speeding-related crashes, such as single-vehicle run-off road crashes, low-speed-limit area, crashes on curves, collision with fixed objects, nighttime crashes, young age, male driver, non–use of seatbelts, driving under the influence of alcohol (DUI) and no or invalid license. Like many existing literatures (Chevalier et al., 2016; McCartan and Elliott, 2018; Tseng et al., 2016), their studies only provided the understanding of factors influencing driver's speeding behaviour (for example, young driver are more aggressive and likely to involving in speeding crash). However, there is still a marginal limited understanding to date of how crash-level factors (including driver characteristic, roadway attribute, vehicle characteristic, crash characteristic or environment and temporal characteristic) of speeding and non-speeding driving-related crashes affect the level of crash severity. Hence, the intent of this study is to fulfil this remaining research gap.

In recent years, researchers recognized temporal instability as one of the major sources of unobserved heterogeneity in the research on injury severity, which requires careful consideration (Mannering, 2018). For example, Behnood and Mannering (2015) examined changes in factors influencing injury severity in drivers involved in single-vehicle crashes over time. The result indicated a wide range of temporally unstable factors caused by the urban nature of data, changes in practices related to police reporting over time, improvement in vehicle safety features, and effect of macroeconomic instability. Moreover, Marcoux et al. (2018) pointed out that many factors, such as policy enforcement, enhanced safety features and technology of vehicles, and education campaign efforts to promote safety, chiefly contribute to the improvement in injury severity related to traffic crashes. Considerable number of frontline studies underscored the growing interest in temporal instability and unobserved heterogeneity in the research on injury severity (Behnood and Mannering, 2019; Li et al., 2021; Yan et al., 2021a; Yu et al., 2021; Zamani et al., 2021). The findings provided evidence that ignoring the influence of temporal instability on levels of injury severity due to crashes could lead to bias and unreliable results or conclusions. With that being said, additional research gap to date is a study to compare between the effects of crash-level factors in crash involving speeding driving with non-speeding driving behaviour on the driver-injury severity in the contexts of both possible temporal instability and unobserved heterogeneity.

The objective of the current study is to investigate the influence of crash-level factors of speeding driving-related crash on the outcomes of driver-injury severity compared with non-speeding driving crashes by carefully accounting for possible temporal instability and unobserved heterogeneity. The finding of this paper could potentially help generating a more effective guidance for policymakers to hit the right targets and effectively reduce road casualties.

3.3 General Findings of Previous Driver-Injury Severities Studies

Table 3.1 provides a summary of variable found to significantly influence driver-injury severity in previous studies. In addition, the table groups variables into the following broad categories including driver characteristics (age, gender, fatigue, alcohol, impaired, seatbelt, and exceeding speed limit) roadway characteristics (horizonal/vertical alignment, median type, pavement type, and road under construction/maintenance), vehicle characteristics (vehicle age, airbag and vehicle type), crash characteristics (overturn, run off road, hitting fixed object and hitting guardrail), environmental characteristics (season information, wet/dry road surface condition, lighting condition and weather condition), temporal characteristics (weekend and various time-of-day such as early morning, peak-hour, and late night), spatial characteristics (urban, rural, district level and region level attributes).

3.4 Data Description

In this study, data on single-vehicle crashes were derived from Highway Accident Information Management System, Thailand (DOH, 2018) over a six years period (from January 1, 2012 to December 31, 2017). The single-vehicle crash is considered as speeding-related crash when police officers identify the driver driving over the posted speed limit, otherwise the crash is considered as non-speeding driving crash. **Figure 3.1** shows the driver-injury severity distributions for speeding and non-speeding driving over three periods (2012–2013, 2014–2015, and 2016–2017). Despite not much variation in the aggregate injury severity totals over period for both speeding and non-speeding driving crashes, interestingly, severe/fatal injury proportions of non-speeding crashes relative to its observation are slightly higher than those in the speeding driving case in all considered time period (the previous work still found a significant temporal instability of parameter estimates across time period despite slight variations were observed (Islam and Mannering, 2020)). **Table 3.2** provides the

Table 3.1 Summary of variables found to be statistically influencing driver injury severities in past crash injury-severity studies

Variable	Previous research
Driver characteristics	
Age	Young drivers are more likely to sustain minor injury (Islam and Mannering, 2020; Xie et al., 2012); Middle age drivers are more likely to sustain no-injury (Islam and Mannering, 2020); Old drivers increase the probability of severe injury (Yu et al., 2021; Gong and Fan, 2017, Al-Bdairi et al., 2018; Se et al., 2021a; Xie et al., 2012)
Gender	Female drivers are more prone to severe injuries than male drivers (Dabbour et al., 2020, Behnood and Mannering, 2015); Male drivers increase the probability of severe and fatal relative to female counter part (Yu et al., 2020a; Yu et al., 2021; Fountas et al., 2020, Se et al., 2021a)
Fatigue	Fatigue drivers increase the likelihood of severe and fatal injury (Behnood and Mannering, 2015; Se et al., 2021a)
Alcohol	Under influence of alcohol drivers increase the probability of severe injury (Xie et al., 2012; Islam and Mannering, 2020; Yu et al., 2021, Se et al., 2021a; Behnood and Mannering, 2015)
Impaired	Impaired drivers are more likely to sustain serious and fatal injury (Yu et al., 2019; Behnood and Mannering, 2015)
Seatbelt usage	Unequipped seatbelt drivers increase the probability of higher injury severity and fatal injury (Yu et al., 2019; Se et al., 2020a, 2020b, 2020c, 2021a; Islam and Mannering, 2020)
Exceeding speed limit	Driving over the speed limit increases the probability of severe injury (Behnood and Mannering, 2015)
Roadway characteristics	
Alignment	Crash on curve road increases the probability of severe injury (Islam and Mannering, 2020; Yu et al., 2021; Gong and Fan, 2017; Al-Bdairi and Hernandez, 2020); crash on graded road increase probability of severe and fatal injury (Se et al., 2021a)

Table 3.1 Summary of variables found to be statistically influencing driver injury severities in past crash injury-severity studies (Cont.)

Variable	Previous research
Median type	Crashes on raised and depressed median road increase the probability of severe and fatal injury (Se et al., 2021a)
Pavement type	Compared to concrete pavement, crashes on asphalt pavement decrease the probability of no and minor injury (Se et at, 2021a)
Construction/ Maintenance	Crash on road under construction or maintenance decrease probability of minor and severe injury (Behnood and Mannering, 2015), other work fount it to increase probability of severe and fatal injury (Se et al., 2021a).
Vehicle characteristics	
Vehicle age	Likelihood of fatalities and evident injury increases with vehicle age (Yu et al., 2019)
Airbag	No airbag and deployed airbag in a crash increase the probabilities of higher injury severities (Yu et al., 2019)
Vehicle type	Crash involving passenger car, Sport Utility Vehicle (SUV) and pick-up truck decreases the likelihood of severer injury (Islam and Mannering, 2020, Yu et al., 2020a, 2021, Se et al., 2021a; Behnood and Mannering, 2015)
Crash characteristics	
Overturn/off-road	Overturn or off-road crashes increase the probability of injury and fatal crashes (Yu et al., 2019; Islam and Mannering, 2021)
Fixed object	Collision with fixed object increases the probability of severe injury (Islam and Mannering, 2020, 2021)
Guardrail	Hitting guardrail while vehicle running off road decreases the probability of severer injury (Se et al., 2021a; Anarkooli et al., 2017; Roque et al., 2015)
Environmental characteristic	
Season	Winter increases the probability of serious and fatal injury (Yu et al., 2019)

Table 3.1 Summary of variables found to be statistically influencing driver injury severities in past crash injury-severity studies (Cont.)

Variable	Previous research
Wet/snow	Wet and snow decrease the probability of injury and fatal crash (Yu et al., 2019; Yu et al., 2020a; Yu et al., 2020b); Dry Road surface increases probability of severe injury (Behnood and Mannering, 2015)
Light condition	Crash during night time on unlit road increases the possibility of severe injury (Behnood et al., 2014; Yu et al., 2020b; Yu et al., 2021; Al-Bdairi et al., 2018, 2020; Islam and Mannering, 2021) and increases probability of no-injury crash (Xie et al., 2012); Crash during night time on lit road decrease probability of severe and fatal injury (Se et al., 2021a)
Weather	Clear weather increases the likelihood of minor and severe injury compared to the unclear counterpart (Al-Bdairi et al., 2020)
Temporal characteristic	
Weekend	Likelihood of severe injury increases for weekend crash (Islam and Mannering, 2020; Se et al., 2021a).
Time-of-day	Crash during morning peak-hour (7:00 to 9:30 AM) increases the probability of higher injury severity (Se et al., 2021a); Crash during early morning (12 AM to 5:59 AM) and late night (9 PM to 11:59 PM) increases probability of no-injury and severe injury (Islam and Mannering, 2021)
Spatial characteristic	
Urban/rural	Compared to rural area, severe and fatal injury crashes are less likely in urban area (Xie et al., 2012; Yu et al., 2019)
District level	Islam and Mannering (2020) found that probability of a certain injury severity could vary from one district to next in Florida.
Region level	Se et al., (2021a) found that probability of a certain injury severity could vary from one region (a group of provinces) to next using data from Thailand.

descriptions and descriptive statistics of the levels of driver-injury severities and the significant explanatory variables. A total of six categories of variable were considered including driver characteristics (age, gender, belt usage, under influence of alcohol and fatigue), roadway attributes (flush/raised/depressed/barrier median, road lane, road under construction, pavement type, road alignment, intersection and U-turn), vehicle types (van, passenger car, pick-up car, and truck), crash characteristics (running off road on straight/curve, running off road on straight/curve and hitting guardrail, and mounting traffic island), environmental and temporal characteristics (wet/dry road surface, rain, lit/unlit road, weekend, morning peak hour, and evening peak hour) and spatial characteristics (central, eastern, northern and southern part of the country).

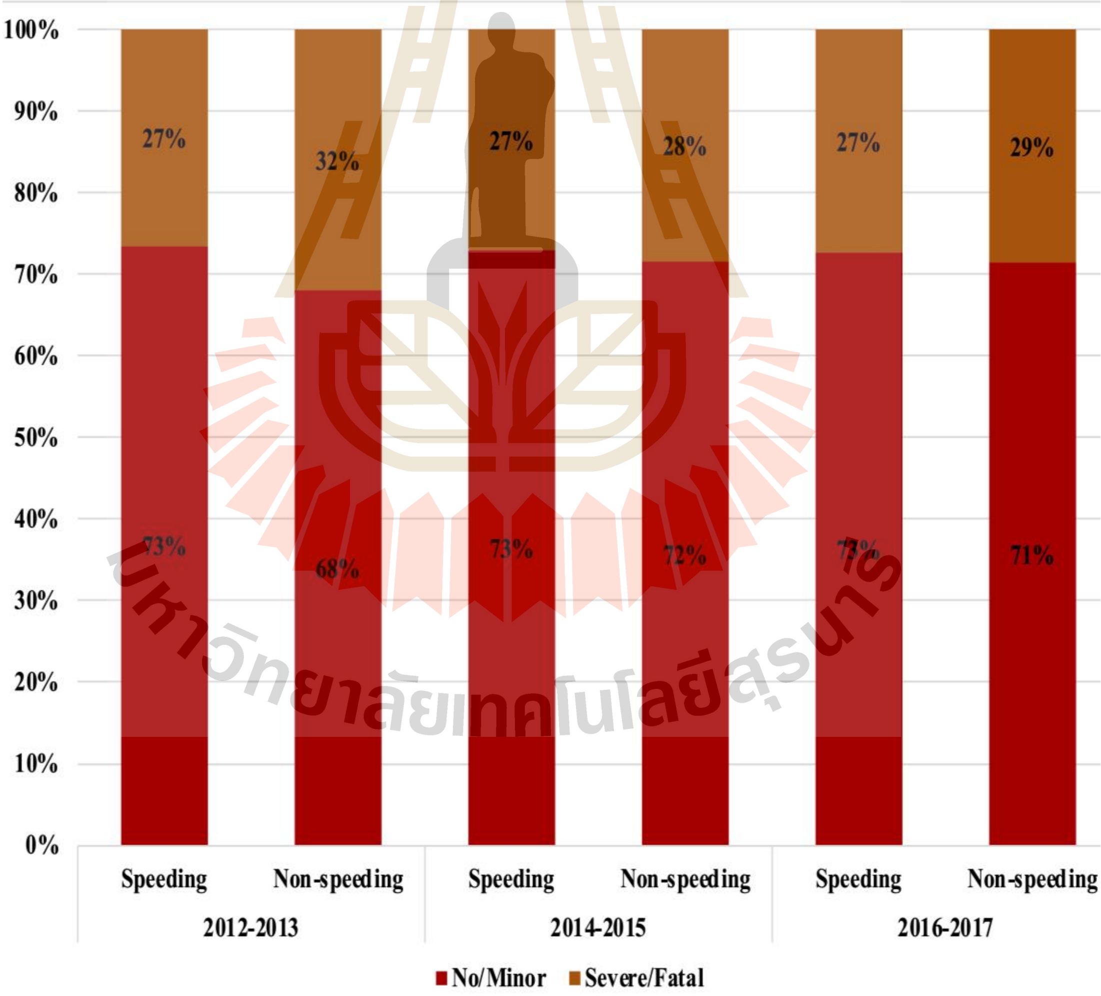

Figure 3.1 Driver-injury severity distributions for speeding and non-speeding driving over the years: 2012–2017

Table 3.2 Descriptive statistic of the significant explanatory variables

Variables	Description	Non-speeding driving			Speeding driving		
		2012-2013	2014-2015	2016-2017	2012-2014	2014-2016	2016-2018
Driver injury		Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
no or minor/ severe or fatal		402/189	525/209	456/182	1470/531	1900/707	1618/611
Driver characteristics							
Young	1 = Age below 26, 0 = otherwise	0.093(0.290)	0.219(0.414)	0.169(0.375)	0.095(0.294)	0.259(0.438)	0.199(0.399)
Old	1 = Age 50 years and above, 0 = otherwise	0.133(0.340)			0.157(0.364)	0.181(0.385)	0.187(0.390)
Male	1 = Male driver, 0 = female driver	0.879(0.325)	0.867(0.338)	0.877(0.327)	0.871(0.335)		
Belt	1 = Uses seatbelt, 0 = otherwise	0.417(0.493)	0.472(0.499)	0.442(0.497)	0.386(0.487)	0.383(0.486)	0.377(0.484)
Alcohol	1 = Under influence of alcohol, 0 = otherwise	0.043(0.205)	0.054(0.227)	0.043(0.205)	0.009(0.097)		
Fatigue	1 = Falling asleep, 0 = otherwise	0.514(0.500)	0.549(0.497)	0.554(0.497)			
Roadway characteristics							
Painted	1 = Painted median road, 0 = otherwise	0.023(0.152)					
Raised	1 = Raised median road, 0 = otherwise			0.211(0.408)		0.255(0.436)	0.245(0.430)
Depressed	1 = Depressed median road, 0 = otherwise	0.384(0.486)				0.339(0.473)	0.362(0.480)
Barrier	1 = Barrier median road, 0 = otherwise			0.068(0.253)	0.028(0.166)	0.045(0.207)	0.055(0.229)
2-lane	1 = Two-lane highway, 0 = otherwise	0.333(0.471)	0.374(0.484)			0.261(0.439)	
4-lane	1 = Four-lane highway, 0 = otherwise		0.520(0.499)			0.611(0.487)	
Construction	1 = Road under construction, 0 = otherwise			0.031(0.174)	0.021(0.146)	0.019(0.138)	0.023(0.152)
Pavement	1 = Asphalt, 0 = concrete	0.937(0.242)	0.937(0.242)			0.925(0.261)	
Curve	1 = Curve road, 0 = otherwise		0.260(0.439)	0.206(0.405)			0.312(0.463)
Grade	1 = Graded road, 0 = otherwise	0.111(0.315)		0.084(0.278)			
Intersection	1 = Within intersection, 0 = otherwise			0.086(0.280)	0.066(0.249)	0.069(0.254)	
U-turn	1 = Within U-turn, 0 = otherwise		0.062(0.242)	0.101(0.302)			

Table 3.2 Descriptive statistic of the significant explanatory variables (Cont.)

Variables	Description	Non-speeding driving			Speeding driving		
		2012-2013	2014-2015	2016-2017	2012-2014	2014-2016	2016-2018
Vehicle characteristics							
Van	1 = Van, 0 = otherwise	0.020(0.141)	0.038(0.191)	0.026(0.161)	0.017(0.132)	0.019(0.137)	0.021(0.146)
Passenger car	1 = Passenger car, 0 = otherwise			0.322(0.467)	0.361(0.480)	0.364(0.481)	0.363(0.481)
Pick-up	1 = Pick-up truck, 0 = otherwise			0.443(0.497)	0.476(0.499)	0.477(0.499)	
Truck	1 = Large-truck, 0 = otherwise		0.183(0.387)	0.180(0.384)	0.124(0.330)	0.123(0.329)	
Crash characteristics							
OOS	1 = Runs off road on straight, 0 = otherwise			0.192(0.394)		0.121(0.326)	
OOSG	1 = Runs off road on straight and hits guardrail, 0 = otherwise	0.314(0.464)	0.307(0.461)	0.358(0.480)	0.325(0.468)	0.320(0.466)	0.333(0.471)
MTI	1 = Mounts traffic island, 0 = otherwise	0.175(0.381)	0.160(0.367)	0.216(0.412)	0.279(0.449)	0.229(0.420)	0.230(0.421)
OOC	1 = Runs off road on curve, 0 = otherwise	0.060(0.239)	0.070(0.256)	0.059(0.236)			
OOCG	1 = Runs off road on curve and hits guardrail, 0 = otherwise	0.181(0.385)	0.164(0.371)		0.183(0.387)	0.214(0.410)	
Environmental and temporal characteristics							
Wet	1 = Wet road, 0 = otherwise	0.093(0.290)		0.089(0.285)	0.219(0.414)	0.219(0.414)	
Rain	1 = Raining, 0 = otherwise	0.113(0.317)		0.097(0.296)		0.232(0.422)	
Unlit road	1 = Unlit road, 0 = otherwise			0.084(0.278)	0.135(0.342)	0.111(0.314)	
Lit road	1 = Lit road, 0 = otherwise			0.379(0.485)		0.366(0.481)	0.371(0.483)
Weekend	1 = Weekend, 0 = weekday			0.299(0.458)		0.311(0.463)	
Morning	1 = Morning peak hour 7:00–9:30, 0 = otherwise		0.080(0.272)	0.065(0.248)		0.075(0.263)	0.082(0.275)
Evening	1 = Evening peak hour 16:00–19:30, 0 = otherwise	0.126(0.333)	0.132(0.338)	0.103(0.304)			
Region characteristics							
Central	1 = Central country, 0 = otherwise			0.202(0.401)	0.191(0.393)	0.182(0.386)	0.202(0.401)
Eastern	1 = Eastern country, 0 = otherwise		0.043(0.204)	0.034(0.182)	0.098(0.298)	0.087(0.283)	0.083(0.277)
Northern	1 = Northern country, 0 = otherwise			0.470(0.499)	0.373(0.483)		
Southern	1 = Southern country, 0 = otherwise	0.214(0.411)		0.202(0.401)	0.263(0.440)	0.262(0.440)	0.253(0.435)

3.5 Methodology

In crash-injury severity analysis, analysts are not able to collect all crash-level factors associated with the observed injury severity, which may be associated with physiological differences between genders, physical characteristics of occupants with different/same age, variability in the effect of passengers in the vehicle, variability in roadway attributes, vehicle features, and even weather and environmental characteristics. These unavailable attributes form up unobserved characteristics or unobserved heterogeneity, which requires careful consideration to obtain nonbiased, reliable, and consistent estimation results (see Mannering et al., 2016 for detail review). To resolve this issue, numerous studies have adopted various unordered and ordered heterogeneity modelling approaches for their analysis that have ability to capture the unobserved effect underlying safety data (Saeed et al., 2017, 2019, 2020a, 2020b; Se et al., 2021a, 2021b; Waseem et al., 2019; Chen et al., 2017, 2019b; Volovski et al., 2017; Ahmed et al., 2017; Yamany et al., 2020). With the increased demand to account for potential unobserved heterogeneity in the statistical analysis of injury severity, some recent frontline studies adopted the random parameters approaches with heterogeneity in means and variances which were able to explored various layer of unobserved heterogeneity and among the most flexible approach in capturing unobserved heterogeneity underlying in crash data (Al-Bdairi et al., 2020; Behnood and Mannering, 2017; Islam et al., 2020; Mannering et al., 2016; Huo et al., 2021). The model initially introduces a function that determines the probability of driver-injury outcomes as follows (Washington et al., 2020):

$$S_{jm} = \boldsymbol{\beta}_j \boldsymbol{X}_{jm} + \varepsilon_{jm} \tag{3.1}$$

where $\boldsymbol{S}_{jm}$ denotes an injury severity function that determines the probability of the level of injury severity j (j = 0, 1, respectively, for no/minor and severe/fatal injury) in crash m, $\boldsymbol{\beta}_j$ pertains to the vector of estimable coefficients, $\boldsymbol{X}_{jm}$ represents the vector of explanatory variables that impact injury severity, and $\boldsymbol{\varepsilon}_{jm}$ stands for the error term. The outcome probabilities of a random parameters logit model can be defined as follows (Washington et al., 2020):

$$\boldsymbol{P_m(j)} = \int \frac{\boldsymbol{EXP(\beta_j X_{jm})}}{\boldsymbol{\sum_{\forall j} EXP(\beta_j X_{jm})}} \boldsymbol{f(\beta|\rho) d\,\beta} \tag{3.2}$$

where $\boldsymbol{P_m(j)}$ stands for the probability of injury severity *j* in crash *m*, $f\boldsymbol{(\beta|\rho)}$ refers to the density function of $\boldsymbol{\beta}$ with ρ being the vector of parameters (mean and variance), and all other terms are as previously defined. To account for the possibility of unobserved heterogeneity in means and variances of random parameters, let $\boldsymbol{\beta}_{jm}$ be a vector of estimated parameters that varies across crashes, which is derived as follows (Washington et al., 2020):

$$\boldsymbol{\beta}_{jm} = \boldsymbol{\beta_j} + \Theta_{jm}\boldsymbol{Z}_{jm} + \sigma_{jm}EXP(\boldsymbol{\omega}_{jm}\boldsymbol{W}_{jm})\nu_{jm} \tag{3.3}$$

where $\boldsymbol{\beta}_j$ refers to the mean parameter estimate across all crashes, $\boldsymbol{Z_{jm}}$ is a vector of the explanatory variable that captures heterogeneity in the mean that influences injury severity *j*, Θ_{jm} represents a vector of estimable parameters, $\boldsymbol{W}_{jm}$ refers to a vector of crash-specific variables that captures heterogeneity in the standard deviation $\boldsymbol{\sigma_{jm}}$ with corresponding vector $\boldsymbol{\omega}_{jm}$, and ν_{jm} is the disturbance term. The model estimations were conducted using a simulated maximum likelihood approach with 1,000 Halton draws and the normal distribution was considered for the function form of parameter density function $f(\beta|\varphi)$ since it generally provided the best model fit (Al-Bdairi et al., 2020; Islam and Burton, 2020). In addition, average marginal effects over all crash observations were computed to capture the effect that a one-unit change in any specific explanatory variable has the probability of an injury severity outcome (i.e., for indicator variables, this is the change in probability resulting from the indicator going from 0 to 1) (Washington et al., 2020).

3.6 Transferability and Temporal Stability Test

The paper conducted two groups of tests to separately examine the difference of driver-injury severity outcomes between speeding and non-speeding driving-related crashes and different time periods (we conducted extensive empirical testing with a combination of various numbers of years for possible temporal instability over time, prioritized the number of observations for each time period, and found that splitting data into 2012–2013, 2014–2015, and 2016–2017 provided the most statistically significant temporal separation) through a series of Likelihood Ratio Tests. First, transferability tests between speeding and non-speeding can be computed using the following equation (Washington et al., 2020):

$$\chi_p^2 = -2[LL(\boldsymbol{\beta}_{combined,p}) - LL(\boldsymbol{\beta}_{speeding,p}) - LL(\boldsymbol{\beta}_{non-speeding,p}), \tag{3.4}$$

where $LL(\boldsymbol{\beta}_{combined,p})$ is the log-likelihood at the convergence of the model that used all data on speeding and non-speeding driving for period p (either 2012–2013, 2014–2015, or 2016–2017). $LL(\boldsymbol{\beta}_{speeding,p})$ and $LL(\boldsymbol{\beta}_{non-speeding,p})$ denote the log-likelihood at the convergence of the model based on data on crashes involving speeding and non-speeding driving, respectively, for period $\boldsymbol{p}$. The X^2 test results of 2012–2013, 2014–2015, and 2016–2017 are 103.10, 66.97, and 50.78 that are χ^2 distributed with 23, 15, and 28 degrees of freedom (dof) equal to the summation of parameters found to be statistically significant in each model minus the number of parameters found to be statistically significant in the model using combined data (Islam et al., 2020)), respectively. These results indicate that the null hypothesis that speeding and non-speeding driving are the same can be rejected with a greater than 99%.

Lastly, we conducted a series of likelihood ratio test to compare the models developed for two individual years and inspect if the parameter estimates are stable between the two years, as follows (Washington et al., 2020):

$$\chi^2 = -2[\mathrm{LL}(\beta_{m_2 m_1}) - \mathrm{LL}(\beta_{m_1})] \tag{3.5}$$

where $LL(\beta_{m_2 m_1})$ is the log-likelihood at the convergence of the model containing significant (converged) parameters from m_2 while using data subset m_1. $LL(\beta_{m_1})$ pertains to the log–likelihood at the convergence of the model using data from subset m_1 with parameters no longer restricted to the converged parameters of subset m_2. The test was also reversed, such that subset m_1 became m_2 and vice versa. To determine the confidence level, χ^2 statistic with a degree of freedom equals to the number of estimated parameters is used on the basis of the rejection or acceptance of the null hypothesis that the parameters are the same between m_1 and m_2. **Table 3.3** presents the result of temporal stability test between two individual years for both speeding and non-speeding models. Despite the non-significance of some test in the model (one in speeding model and one in non-speeding model; **Table 3.3**), the overall test result still indicates the significant presence of temporal instability across models for 2012–2013, 2014–2015, and 2016–2017. To be precise, using the converged parameters of 2014–2015 or 2016–2017 as the starting values and applying them to the 2012–2013 data gave [$\chi^2; dof$] values of [53.26; 37] and [65.56; 25], respectively, in the speeding model and [63.49; 18] and [67.98; 30], respectively, in the non-speeding model, illustrating that the null hypothesis that the pairs 2012–2013 vs 2014–2015 and 2012–2013 vs 2016–2017 (in both speeding and non-speeding models) are the same can be rejected at a 95% confidence level. In addition, using the converged parameters of 2016–2017 as the starting values and applying them to the 2014–2015 data produced [$\chi^2; dof$] values of [62.27; 25] and [49.95; 30], respectively, in the speeding and non-speeding driving models, giving a confidence level higher than 95% to reject the null hypothesis that the two time periods are the same.

3.7 Result and Discussion

The results of the models for driver-injury severities of the non-speeding and speeding driving crashes are presented in **Table 3.4** and **Table 3.5**, respectively. **Table 3.6** presents the summary of the marginal effects of the explanatory variables across time period for both speeding and non-speeding driving models, which will be used for comparison of temporal instability of the significant factors. The goodness-of-fit (ρ^2) of 2012–2013, 2014–2015 and 2016–2017 models for non-speeding driving models are 0.165, 0.182 and 0.128, respectively, and for speeding models are 0.078, 0.073 and 0.077, respectively. Despite the relatively small value, it remains in acceptable criterion (Alnawmasi and Mannering, 2019; Champahom et al., 2020a, 2020b).

3.7.1 Heterogeneity in mean and variance

Regarding, unobserved factors, it should be noted that negative mean value of random parameter imply that majority of the observations are less likely to sustain severe or fatal injury; whereas positive mean value indicate that majority of the observations have higher possibility of sustaining severe or fatal injury.

Table 3.3 Temporal stability test among different period models (degree of freedom in brackets and confidence level in parenthesis)

m1/m2	Non-speeding driving			Speeding driving		
	2012-2013	**2014-2015**	**2016-2017**	**2012-2013**	**2014-2015**	**2016-2017**
2012-2013	-	63.49 [18] (99.99%)	67.98 [30] (99.99%)	-	53.26 [37] (95.94%)	65.56 [25] (99.99%)
2014-2015	44.02 [25] (98.92%)	-	49.95 [30] (98.74%)	46.07 [30] (96.94%)	-	62.27 [25] (99.99%)
2016-2017	14.54 [25] (0.05%)	33.73 [18] (98.64%)	-	53.92 [37] (96.43%)	29.4 [37] (0.19%)	-

Table 3.4 Estimated parameter results of non-speeding driving models (Bold values indicate random parameters)

Variables	2012-2013	2014-2015	2016-2017
	Coefficient(t-stat)	Coefficient(t-stat)	Coefficient(t-stat)
Constant	4.881(3.12)	-	**5.654(1.78)**
SD "Constant"	-	-	***3.367(4.13)***
Driver characteristic			
Young	-1.279(-1.98)	**-3.281(-4.08)**	2.234(2.57)
SD "Young"	-	***7.032(5.68)***	-
Old	-2.680(-3.65)	-	-
SD "Old"	-	-	-
Male	-2.013(-3.71)	0.607(2.22)	**-18.124(-4.5)**
SD "Male"			***41.736(4.64)***

Table 3.4 Estimated parameter results of non-speeding driving models (Bold values indicate random parameters) (Cont.)

Variables	2012-2013	2014-2015	2016-2017
	Coefficient(t-stat)	Coefficient(t-stat)	Coefficient(t-stat)
Belt	**-6.085(-5.53)**	-0.695(-4.06)	-3.348(-3.56)
SD "Belt"	***12.873(6.55)***		-
Alcohol	**0.473(0.29)**	0.521(1.73)	7.336(3.68)
SD "Alcohol"	***16.878(4.55)***	-	-
Fatigue	**-1.373(-2.38)**	-	6.123(4.26)
SD "Fatigue"	***16.955(6.66)***	-	-
Roadway characteristic			
Painted median	2.723(2.17)	-	-
Raised median	-	-	-1.732(-1.9)
Barrier median	-	-	11.483(4.15)
2-lane	-	1.261(3.48)	-
4-lane	-	1.075(3.05)	-
Construction	-	-	-4.449(-2.33)
Pavement	-1.370(-2.24)	-1.236(-3.31)	-
Curve	-	-	
Grade	-1.448(-1.95)	-	5.678(3.24)
Intersection	-	-	-10.661(-3.84)
U-turn	-	-	2.435(1.79)
Vehicle characteristic			
Van	6.029(2.77)	0.954(2.11)	9.843(2.92)
Passenger car	-	-	-11.260(-3.65)
Pick-up	-	-	-15.552(-4.06)
Truck	-	**-1.533(-2.17)**	-16.368(-4.04)
SD "Truck"	-	***5.574(5.16)***	-
Crash			
OOSG	-3.569(-4.43)	-1.106(-4.01)	-2.693(-2.15)
MTI	-2.514(-3.27)	-0.820(-2.66)	-

Table 3.4 Estimated parameter results of non-speeding driving models (Bold values indicate random parameters) (Cont.)

Variables	2012-2013	2014-2015	2016-2017
	Coefficient(t-stat)	Coefficient(t-stat)	Coefficient(t-stat)
OOC	-	-	7.929(2.70)
OOCG	-1.769(-2.22)	-1.083(-3.42)	-
Environmental and temporal characteristic			
Wet	-6.411(-4.32)	-	-5.017(-1.90)
Rain	4.894(4.04)	-	-6.479(-2.37)
Unlit	-	-	-3.070(-2.60)
Lit road	-	-	1.531(2.02)
Weekend	-	-	1.296(1.74)
Morning	-	0.716(2.60)	4.080(2.65)
Evening	0.986(1.87)	-0.605(-1.96)	-4.670(-3.29)
Spatial characteristic			
Central	-	-	2.339(1.89)
Eastern	-	0.808(1.82)	-11.654(-2.91)
Northern	-	-	2.782(2.35)
Southern	1.542(2.09)	-	9.384(4.06)
Heterogeneity in means			
Belt : 2-lane	-1.747(-1.96)	-	-
Belt : Depressed	4.544(4.52)	-	-
Alcohol : 2-lane	4.969(2.04)	-	-
Fatigue : Depressed	-4.943(-4.67)	-	-
Young : Fatigue	-	0.992(1.69)	-
Young : U-turn	-	3.687(3.24)	-
Young : OOC	-	4.366(2.95)	-
Gender : Curve	-	-	13.161(2.35)
Gender : OOS	-	-	13.241(4.14)
Heterogeneity in variances			
Belt : OOC	0.422(2.06)		

Table 3.4 Estimated parameter results of non-speeding driving models (Bold values indicate random parameters) (Cont.)

Variables	2012-2013	2014-2015	2016-2017
	Coefficient(t-stat)	Coefficient(t-stat)	Coefficient(t-stat)
Fatigue : OOC	-40.508(-159.92)		
Young : Curve		-0.495(-2.17)	
Truck : Curve		-10.029(-39.7)	
Gender : MTI			-0.127(-2.09)
Model Statistic			
N	591	734	638
LL (constant only)	-370.389	-438.473	-381.434
LL (β)	-309.255	-358.727	-332.438
ρ^2	0.165	0.182	0.128

For 2012–2013 non-speeding model, seatbelt use (mean = –6.085; SD = 12.873), DUI (mean = 0.473; SD = 16.878) and fatigue (mean = –1.373; SD = 16.955) indicator produced statically significant random parameters. Regarding heterogeneity in mean, 2-lane road decreased mean of seatbelt indicator (thereby decreasing probability of severe/fatal injury) and increased mean of alcohol random parameter (increasing probability of severe/fatal injury). Similarly, depressed median indicator increased mean of seatbelt use (making no/minor injury less likely) and decreased mean of fatigue random parameter (making no/minor injury more likely). For heterogeneity in variance, run-off road on curve increased the variance of seatbelt use indicator (make the distribution wider) and decreased the variation of fatigue random parameter. This shows a dispersion of random parameters of belted and fatigued drivers across observation, thus indicating a more flexibility to identify the underlying observed heterogeneity by allowing possible heterogeneity in variance of the random parameters.

In 2014–2015 non-speeding model, only two parameters resulted in significant random parameters: young driver (mean = –3.281; SD = 7.032) and truck indictor (mean = –1.533; SD = 5.574). Fatigue, U-turn and run-off-road on curve (OOC)

Table 3.5 Estimated parameter results of speeding driving models (Bold values indicate random parameters)

Variables	2012-2013 Coefficient(t-stat)	2014-2015 Coefficient (t-stat)	2016-2017 Coefficient(t-stat)
Driver characteristics			
Young	**-28.903(-4.9)**	0.354(2.71)	-
SD "Young"	***34.620(6.09)***	-	-
Old	0.350(2.36)	**0.756(3.83)**	-
SD "Old"	-	***1.309(6.9)***	-
Male	0.461(2.54)	-	-
Belt	-0.207(-1.77)	**-0.637(-3.76)**	-0.284(-2.32)
SD "Belt"	-	***0.429(3.41)***	-
Alcohol	1.831(3.26)	-	-
Roadway characteristics			
Raised median	-	0.490(3.27)	0.393(2.45)
Depressed median	-	0.540(4.02)	0.264(1.75)
Barrier median	0.757(2.27)	**-52.312(-2.5)**	1.201(4.98)
SD "Barrier"	-	***168.411(2.62)***	-
2-lane	-	-0.348(-1.93)	-
4-lane	-	**-1.016(-4.92)**	-
SD "4-lanes"	-	***3.522(18.26)***	-
Construction	-	0.538(1.67)	0.742(2.06)
Pavement	-	**-0.862(-4)**	-
SD "Pavement"	-	***2.612(19.26)***	-
Curve	-	-	0.737(2.45)
Intersection	-	-0.416(-1.88)	-
Vehicle characteristics			
Van	-1.153(-2.47)	**-59.405(-2.5)**	-1.073(-2.14)
SD "Van"	-	***103.684(2.56)***	-
Passenger car	**-1.491(-2.99)**	-1.174(-3.24)	-1.070(-3.22)
SD "Passenger car"	***2.890(12.1)***	-	-

Table 3.5 Estimated parameter results of speeding driving models (Bold values indicate random parameters) (Cont.)

Variables	2012-2013 Coefficient(t-stat)	2014-2015 Coefficient (t-stat)	2016-2017 Coefficient(t-stat)
Pick-up	**-0.887(-1.96)**	-1.250(-3.48)	-1.057(-2.28)
SD "Pick-up"	***1.766(12.19)***	-	-
Truck	-1.119(-3.22)	-1.153(-3.04)	-
SD "Truck"			
Crash characteristics			
OOS	-	1.208(4.53)	-
OOSG	-1.125(-4.17)	-1.134(-4.63)	**-1.897(-3.67)**
SD "OOSG"	-	-	***4.638(11.72)***
MTI	-1.434(-5.18)	-1.192(-4.65)	**-2.177(-3.56)**
SD "MTI"	-	-	***5.698(9.71)***
OOCG	-0.787(-2.57)	-1.169(-3.41)	-
Environmental and temporal characteristics			
Wet	-	-1.065(-2.85)	-
Rain	-	0.874(2.41)	-
Unlit	**-8.362(-5.59)**	0.314(1.83)	-
SD "Unlit"	***8.985(8.33)***	-	-
Lit road	-	-	-0.293(-2.32)
Morning	-	-	**-5.635(-3.06)**
SD "Morning"	-	-	***33.123(6.57)***
Evening	-	-	-
Spatial characteristics			
Central	1.038(3.96)	0.680(2.62)	0.635(2.14)
Eastern	0.830(2.88)	0.491(1.70)	1.008(3.02)
Northern	0.566(2.28)	-	-
Southern	0.711(2.81)	1.125(4.52)	0.651(2.31)
Heterogeneity in mean			
Young : Wet	15.337(5.54)	-	-

Table 3.5 Estimated parameter results of speeding driving models (Bold values indicate random parameters) (Cont.)

Variables	2012-2013 Coefficient(t-stat)	2014-2015 Coefficient (t-stat)	2016-2017 Coefficient(t-stat)
Young : Intersection	8.597(3.39)	-	-
Unlit :Wet	-1.883(-2.74)	-	-
Unlit : Intersection	3.335(3.25)	-	-
Unlit : Construction	6.258(3.40)	-	-
Old : Lit road	-	-1.045(-3.43)	-
Belt : Lit road	-	0.974(4.18)	-
Barrier : Lit road	-	15.993(2.34)	-
4-lane : Weekend	-	0.426(1.92)	-
Van : Lit road	-	46.497(2.5)	-
Van : Morning	-	37.551(2.31)	-
MIT : Young	-	-	-0.885(-2.18)
Morning : Young	-	-	-5.599(-3.57)
Morning : Old	-	-	-7.574(-3.79
Model statistic			
N	2001	2607	2229
LL (constant only)	-1157.771	-1523.640	-1309.109
LL (β)	-1067.786	-1412.233	-1208.232
ρ^2	0.078	0.073	0.077

indicators increased the mean of young driver indicator, thus increasing likelihood of severe/fatal injury. Besides, crashes on curve road indicator were found to decrease the variance of both young driver and truck indicators.

In 2016–2017 non-speeding model, constant term (mean = 5.654; SD = 3.367) and male driver indicator (mean = –18.124; SD = 41.736) resulted in significant random parameters. Crashes occurring on curve and vehicle running off road on straight road indicator increased the mean of male random parameter, thereby increasing the chance of severe/fatal injury. Vehicle mounting traffic island indicator decreased variation of male driver random parameters.

Move to 2012–2013 speeding driving model, young driver (mean = –28.903; SD = 34.62), passenger car (mean = –1.491; SD = 2.890), pickup truck (mean = –0.887; SD = 1.766) and unlit road (mean = –8.362; SD =8.985) resulted in significant random parameters. Wet road and intersection area indicator increased means young driver random parameter, thus increasing likelihood of severe/fatal injury. Likewise, intersection and road under construction increase means unlit road indicator, making severe/fatal injury more likely. On the other hand, wet road indicator decreased the mean of unlit road random parameter, thus making no/minor injury more likely.

In 2014–2015 speeding model, six significant random parameters were found including old driver (mean = 0.756; SD = 1.309), restrain (mean = – 0.637; SD = 0.429), barrier median (mean = –52.312; SD = 168.411), 4–lane road (–1.016; SD = 3.522), pavement (mean = –0.862; SD = 2.612) and van (mean = –59.405; SD = 103.684). Lit road decreased the mean of old driver random parameter, thereby increasing possibility of no/minor injury. In contrast, severe/fatal injury become more probable as result of lit road increased mean of seatbelt use, barrier median, and van random parameter. Additionally, morning indicator also increased mean of van, making no/minor injury less likely.

In 2016–2017 speeding model, three parameters resulted in significant random parameters: run–off road on straight and hitting guardrail (OOSG, mean = –1.897; SD = 4.638), mounting traffic island (MTI, mean = –2.177; SD = 5.698), and morning indicator (mean = –5.635; SD = 33.123). Young driver decreased mean of MTI, thereby increasing probability of no/minor injury. Likewise, young and old driver decreased mean of morning random parameter, thus decreasing probability of being sustaining severe/fatal injury.

3.7.2 Effect of driver characteristics

As indicated in **Table 3.6**, young driver was found to be relatively unstable for both speeding and non-speeding models. For speeding driving model, the marginal effect of this indicator changed from decreasing in the 2012–2013 model to increasing the probability of severe/fatal injury in the 2014–2015 model. Likewise, for non-speeding model, the marginal effect shifted from negative effect in 2012–2013 and 2014–2015 to positive effect on severe/fatal injury in 2016–2017. Such result is to some extent agree with Behnood and Al-Bdairi (2020). The shifting in marginal effect value may be possibly due to the changes in attitudes of young driver that may in turn result in increases of risky driving behaviour among young driver incrementally over time (Mannering et al., 2016). However, Islam and Mannering (2020) found that young drivers stably decrease the likelihood of severe injury (2016 and 2017). This could be due to different nature of the data source used in each study (both spatial and temporal) (Alnawmasi and Mannering, 2019).

Regarding old driver, the marginal effect showed an increased probability of severe/fatal injury to the driver during 2012–2013 and 2014–2015, whereas it was found to be non–significant in the 2016–2017 for speeding model. In contrast, old driver was found to increase the chance of no/minor injury during 2012–2013 for the non-speeding driving model, but was found to be insignificant during the later period. The finding is intuitive and consistent with previous studies (Gong and Fan, 2017, Al-Bdairi et al., 2018; Se et al., 2021a; Xie et al., 2012; Ahmad et al., 2019), and even though older drivers were not found to be statically significant in the 2016–2017 speeding driving model, more safety strategies have to be formulated to improve safety for old driver parties regarding their decline in perception and reaction (Islam and Burton, 2020; Yan et al, 2021b). The reason of this instability maybe due to old drivers tend to newer vehicle with constant improvement of vehicle safety feature (such as braking system, airbag, seatbelt and other smart alerting system and so on) and their adaption to them (Behnood and Mannering, 2015; Se et al., 2021a).

In the speeding model, male drivers were found to be statistically significant in only 2012–2013 with an increased risk of severe/fatal injury. On the other hand, in the non-speeding driving model, marginal effect shows instability effect of male driver which decreasing injury severity in 2012–2013, increasing injury severity in 2014–2015, and finally decreasing injury severity once again in 2016–2017. Such complexity effect on injury severity generated by male driver has also been confirmed in a number of previous works (Behnood and Al-Bdairi, 2020; Behnood and Mannering, 2019). A possible explanation for the 2012–2013 finding is that male drivers may be likely to be more aggressive (thus speeding), overuse drug/alcohol, and take risky behaviour when comparing to the female driver counterpart (these findings agree with a previous work result during 2011–2013 (Yan et al., 2021b)). In addition, the reason that this variable became insignificant in later period of speeding crash, is probably due to effort of various safety campaigns and strict law enforcement (on speeding and drunk driving) starting from that period, which make male indicator significant only in all period of non-speeding crash (Behnood and Mannering, 2015)

Seatbelt had stable effect across all time periods for both speeding and non-speeding crash models. The findings are intuitive that using a seatbelt while driving helps the occupant to reduce the risk of sustaining severe/fatal injury (Islam and Mannering, 2020, 2021). Considering the stability effect in decreasing probability of higher injury severity, seatbelt usage should be continuously promoted through various safety campaign efforts (Nambulee et al., 2019; Yu et al., 2020b).

For driver under influence of alcohol, it was found to be statistically significant in only 2012–2013 of the speeding model. However, this indicator was found to be statistically significant in all time periods for the non-speeding driving model with the stable effect that increases the probability of severe/fatal injury which is consistent with previous work (Yu and Long, 2021; Lasota et al., 2020). The reason that alcohol-related drivers are not significant in the 2014–2015 and 2016–2017 speeding models may be attributed to the effect of new law enforcement on drunk driving in the Road Traffic Act (2014) (indicates that police/traffic officers are authorized to stop a vehicle and test whether driver is driving while being drunk, and if driver fails this sobriety test, the driver is assumed to be ‘‘driving while drunk” and will be prosecuted according to the law) that may result in a decline of the number of drunk drivers speeding on the highway. Despite being significant in only non-speeding driving crash model, the effect of alcohol usage still increases the possibility of being severely injured or killed in the crashes. Therefore, this should be one of the prime focuses in improving road safety. Lastly, fatigued drivers were found to increase the risk of severe/fatal injury for only the non-speeding crash model in two time periods including 2012–2013 and 2016–2017. This finding also agrees with the previous works (Behnood and Mannering, 2015; Se et al., 2021a). Regarding these results, it is safe to conclude that alcohol-related driving and being fatigued while driving remain a serious safety issue even for non-speeding driving despite the past efforts. Some implementations can be done to reduce number of drink-driving accident such as increase in number of random breath tests check points, driving-offense point and duration of license disqualification. These elements were found to positively correlated with a deterrence of drink-driving (Chen et al., 2019a). From another perspective, Saeed et al. (2020b) recommended that alcohol-related traffic safety issues could be resolved at a wider spatial scale that goes beyond intersections, road segments, and even singular spatial units through appropriate and effective safety intervention programs to mitigate alcohol-related driving crashes.

3.7.3 Effect of roadway characteristics

In terms of median type (**Table 3.6**), crash on painted median road was found significant in only 2012–2013 non-speeding model, with higher possibility of severe/fatal injury. The reason that this indicator became insignificant in later periods and other models, may be due to the new policy in Thailand to replace and reduce number painted median road with other type of median road across the country. For speeding-related crash, crash on the road with raised median was found to increase the risk of severe/fatal injury during 2014–2015 and 2016–2017, whereas it is more likely to decrease injury severity in 2016–2017 for non-speeding crash. In addition, crash on barrier median road shows relatively unstable effect across three periods for the speeding model (increasing injury severity in 2012–2013 and 2016–2017 and decreasing injury severity in 2014–2015 for majority of the observations). For the non-speeding model, it was also found to increase the probability of severe/fatal injury during the period 2016–2017. Se et al. 2021a, 2021b) reported similar result. The possible explanation for these effects of raised and barrier medians is that its main purposes are to calm the traffic and lower the speed of the vehicle in an urban area. And as expected, exceeding the speeding crashes on raised median could lead to higher injury severity due to high impact hit median (acts as fixed and rigid object). On the other hand, crashes on depressed median road were significant in only the speeding model that make severe/fatal injury more likely to the driving during 2014–2015 and 2016–2017. A possible reason is that depressed median is generally for rural road that serves higher speed limit than urban area; therefore, speeding crashes within depressed median road intuitively generates higher crash impact (Xie et al., 2012; Yu et al., 2019).

Accidents on both two lanes and four lanes were found to decrease injury severity for the speeding driving model, whereas these factors increased the likelihood of severe/fatal injury for the non-speeding crash model in only 2014–2015. To explain the non-speeding model result, the study conducts a Pearson correlation test among the explanatory factor and found that two–lane road crash is significantly positively correlated with older driver, DUI, and running off roadway on curve, whereas four-lane road crash generates a significantly positive correlation with fatigued driver. These are risk factors that are likely to increase the severity of the accident that may explain this result to some extent. However, the cause of this instability (insignificant in other periods) is not necessarily clear which may require further in-depth investigation.

Crash occurring on road under construction was found to significantly increase the risk of higher level of injury severity for the 2014–2015 and 2016–2017 speeding crash models, whereas decrease the risk of severe/fatal injury for the 2016–2017 non-speeding model. The finding is intuitive because operating vehicle with higher speed would increase impact of the crash and significantly increase likelihood of higher injury severity especially when hitting with fixed object (that used in road construction) and consistent with the previous works (Se et al., 2020a, 2021a).

For both speeding and non-speeding models, accidents on the asphalt pavement are less likely to sustain higher injury severity during the periods 2012–2013 and 2014–2015, which is in line with previous studies (Se et al., 2021a). Crashes occurring on curve road section were found to increase the probability of severe/fatal injury for only the speeding driving model during 2016–2017 (also consistent with previous works (Islam and Mannering, 2020; Gong and Fan, 2017; Al-Bdairi and Hernandez, 2020)). For crashes on road on grade, it generates unstable effect for both speeding and non-speeding models. For example, it is only significant in only the 2012–2013 model with positive effect on severe/fatal injury, and it was found to decrease injury severity for non-speeding crash in 2012–2013 and shifted to increase the risk of severe/fatal injury in 2016–2017, which is also consistent with finding of Se et al.

(2021a) that found that vertical alignment of the road could increase the probability of severe and fatal injury. Similarly, Chen et al. (2019a) also reported that fatal crashes are more sensitive to average vertical grade. Crashes within the intersection were found to reduce the risk of severe/fatal injury for both speeding driving (2014–2015) and non-speeding driving model (2016–2017). This is probably due to risk compensation of the driver that tend to drive more carefully and safer when approaching the intersection (Se et al. 2021a). Interestingly, crashes within the U-turn area were found to increase the risk of severe/fatal injury for the 2016–2017 non-speeding driving model. A possible explanation is that the driver involving the non-speeding crash at the U-turn may have already been subjected to a dangerous characteristic such as being drunk, fatigued, or driving an older vehicle. However, the cause of this instability of these indicators (insignificant in other particular period) is also unclear which may require a more in-depth investigation.

3.7.4 Effect of vehicle characteristic

In terms of vehicle types (**Table 3.6**), van drivers were significant in all periods for both speeding and non-speeding models with relatively stable effect across the three time periods. For the speeding driving model, van drivers were less likely to sustain severe/fatal injury in all periods, whereas it significantly increased injury severity for drivers who involved in non-speeding driving crashes. The result may appear counterintuitive; however, there are some possible explanations that would support the finding. In the context of Thailand, transportation company owners (stakeholders) generally install a global positioning system (GPS) for speed tracking to prevent drivers from exceeding the speed limit and to avoid being charged by the police. However, vans or minibuses owned by private companies are generally old vehicles, have low-quality safety features and braking system, lack airbag protection, and so on. On the contrary, the effect of van indicator on driver for the speeding driving model may be captured by private owners whose van is generally newer, having a better safety feature such as good quality braking system, seatbelt, and effective number of airbag deployment that may help driving mitigate higher level of severity even though the crash impact is higher than those by the old van vehicle (Se et al., 2021a). However, without mentioning speeding behaviour of the driver, Weiss et al. (2014) reported that young van driver had higher probability of sustaining serious and fatal injury. This indicated that separating the crash analysis based on speeding behaviour of the driver may potentially help capturing the true effect (unobserved heterogeneity) of van on driver injury severity, thus providing a more accurate guidance for policy formulation to improve driver safety.

Passenger car and pick-up truck generated relatively stable effect across the three considered periods for the speeding driving model, whereas they were significant in only 2016–2017 for the non-speeding model. Overall, the passenger car and pickup truck drivers are more likely to sustain no/minor injury for both speeding and non-speeding models. In addition, in the non-speeding driving model, truck drivers were found to be less likely to sustain severe/fatal injury across all time periods. Interestingly, the same thing occurs in only the first two periods in the speeding model, 2012–2013 and 2014–2015; however, it was found that truck drivers increase the risk of involving into severe/fatal crash in 2016–2017 with marginal effect of 0.7288 (majority of the observations had higher probability of severe/ fatal injury). These results for both models are consistent with previous studies' finding (Islam and Mannering, 2020, Yu et al., 2020a, 2021, Se et al., 2021a; Behnood and Mannering, 2015) and may be due to the incremental improvement of vehicle technology with respect to safety features in vehicles (Behnood and Mannering, 2015; Islam et al., 2020; Mannering, 2018).

3.7.5 Effect of crash characteristic

Regarding crash characteristic (**Table 3.6**), run-off road on straight crashes were found to increase the risk of severe/fatal injury in only the speeding crash model during 2014–2015, whereas running off road on straight and hitting guardrail were found to be significant across all three periods in both speeding and non-speeding crash models which decreased the risk of sustaining severe/fatal injury. On the other hand, vehicle that mounts the traffic island was found to increase the probability of no/minor injury across all periods for all models (except for the 2016–2017 non-speeding model). In addition, running off road on curve and hitting guardrail are significant only in two periods, namely, 2012–2013 and 2014–2015, for both speeding and non-speeding models and increase possibility of no/minor injury. These stable findings are intuitive considering the importance of guardrail that may significantly reduce crash impact as well as resultant injury severity. In addition, numerous studies reported similar result regarding the effect of hitting guardrails on roadside (Anarkooli et al., 2017; Roque et al., 2015; Se et al., 2020a, 2020b, 2021c).

3.7.6 Effect of environmental and temporal characteristics

As shown in **Table 3.6**, crashes on wet road were found to be significant in only 2014–2015 for the speeding model and 2012–2013 and 2016–2017 for the non-speeding model, making no/minor injury more likely. Numerous studies reported similar result and provided explanation that drivers may be more careful while driving on wet road surface (risk compensation) (Yu et al., 2019; Yu et al., 2020a; Yu et al., 2020b, Waseem et al., 2019). In contrast, crashes occurring during rain increase the risk of severe/fatal injury in 2014–2015 (speeding model) and 2012–2013 (non-speeding model). Similarly, Naik et al. (2016) also reported that rainy weather was associated with more severe crash injuries in single-vehicle crashes. Interestingly, for the non-speeding model, the effect of rain indicator shifted to increase the likelihood of no/minor injury in 2016–2017. Again, the reason of instability across time period of wet and rain indicators is unclear which may need a more comprehensive crash dataset that may offer more in-depth investigation.

Regarding nighttime, crashes on unlit road were found to decrease the risk of higher injury severity in 2012–2013 but increase it in 2014–2015 for the speeding driving model. This indicator was not significant in the 2016–2017 speeding driving model, but was found to be statistically significant in reducing the risk of severe/fatal injury in 2016–2017 for non-speeding crashes. On the other hand, crashes during nighttime with light condition generate positive effect on severe/fatal injury for the speeding model but decrease it for the non-speeding model in 2016–2017, indicating that driving with excessive speed could lead to higher injury severity even driving on lit road. It is noteworthy that the effect of darkness resulted in conflict among existing work. Some studies found darkness to increase probability of severer injury (Behnood et al., 2014; Yu et al., 2020b; Yu et al., 2021; Al-Bdairi et al., 2018, 2020; Islam and Mannering, 2021), other found it to decrease possibility of severer injury (Xie et al., 2012). Once again, this is probability due to different methodological approaches, -

Table 3.6 Summary of marginal effect (Bold values indicate random parameters)

Variable	Non-speeding driving			Speeding driving		
	2012-2013	2014-2015	2016-2017	2012-2014	2014-2016	2016-2017
Driver characteristics						
Young	-0.0699	**-0.2803**	0.0286	**-0.2284**	0.0383	-
Old	-0.1314	-	-	0.0501	**0.0879**	-
Male	-0.1332	0.0757	**-0.3121**	0.0585	-	-
Belt	**-0.2551**	-0.0932	-0.0365	-0.0281	**-0.0638**	-0.0293
Alcohol	**0.0296**	0.0749	0.1000	0.3012	-	-
Fatigue	**-0.0801**	-	0.0566	-	-	-
Roadway characteristics						
Painted median	0.19323	-	-	-	-	-
Raised median	-	-	-0.0172	-	0.0538	0.0425
Depressed median	-	-	-	-	0.0584	0.0279
Barrier median	-	-	0.1459	0.1167	**-0.1662**	0.1476
2-lane	-	0.1725	-	-	-0.0349	-
4-lane	-	0.1397	-	-	**-0.1117**	-
Construction	-	-	-0.0293	-	0.0630	0.0872
Pavement	-0.0395	-0.1899	-	-	**-0.1056**	-
Curve	-	-	-	-	-	0.0786
Grade	-0.0784	-	0.0717	-	-	-
Intersection	-	-	-0.0527	-	-0.0399	-
U-turn	-	-	0.0316	-	-	-
Vehicle characteristics						
Van	0.46988	0.1440	0.1364	-0.1210	**-0.1664**	-0.0912
Passenger car	-	-	-0.0974	**-0.1830**	-0.1158	-0.1098
Pick-up	-	-	-0.1327	**-0.1172**	-0.1311	-
Truck	-	**-0.1743**	-0.0722	-0.1255	-0.0980	-
Crash characteristics						

Table 3.6 Summary of marginal effect (Bold values indicate random parameters) (Cont.)

Variable	Non-speeding driving			Speeding driving		
	2012-2013	**2014-2015**	**2016-2017**	**2012-2014**	**2014-2016**	**2016-2017**
OOS	-	-	-		0.1608	-
OOSG	-0.1959	-0.1386	-0.0258	-0.1423	-0.1114	**-0.1936**
MTI	-0.1359	-0.1011	-	-0.1720	-0.1084	**-0.1942**
OOC	-	-	0.1017	-		-
OOCG	-0.0961	-0.1294	-	-0.0964	-0.1077	-
Environmental and temporal characteristics						
Wet	-0.18944	-	-0.0342	-	-0.0970	-
Rain	0.3608	-	-0.0399	-	0.1012	-
Unlit road	-	-	-0.0264	**-0.2409**	0.0347	-
Lit road	-	-	0.0169	-	-	-0.0302
Weekend	-	-	0.0154	-	-	-
Morning	-	0.1048	0.0551	-	-	**-0.2061**
Evening	0.0631	-0.0756	-0.0326	-	-	-
Spatial characteristics						
Central	-	-	0.0288	0.1559	0.0783	0.0706
Eastern	-	0.1196	-0.0488	0.1259	0.0563	0.1202
Northern	-	-	0.0293	0.0788	-	-
Southern	0.0971	-	0.1084	0.1024	0.1315	0.0715

different number of observation/crash level factors, different point in time of data collection and different location of data collection used in each study (Alnawmasi and Mannering, 2019). Crashes on weekend were found to be significant in only one model, 2016–2017, which make severe/fatal injury more likely to driver for the non-speeding driving model (also in line with existing work (Islam and Mannering, 2020; Se et al., 2021a)). Regarding crashes during morning peak hour, it decreases the likelihood of severe/fatal injury for speeding driving in 2016–2017 (53.42% of the observation for no/minor injury, Table 3.5). However, in non-speeding driving crashes, it was found to increase the risk of severe/fatal injury in the 2014–2015 and 2016–2017 models. Crashes during evening peak hour increased risk of higher injury severity in 2012–2013, but decrease it during later period. Some of the findings may appear counterintuitive. Similar to the abovementioned explanation (regarding van driver result), a possible reason for such finding may be that the majority of cases for speeding-related crashes may involve a newer vehicle, thereby containing a better safety feature than those for non-speeding crashes. Additionally, non-speeding crash-related driver may be more likely to subject to risky characteristic such as being fatigued, under the influence of alcohol, or being older driver, thereby additionally explaining the result regarding the nighttime crash. Although, the underlying reason behind the observed instability of these factors is unclear, the result clearly showed temporal instability of these factor across the three considered periods.

3.7.7 Effect of region characteristics

For crashes involving speeding driving (**Table 3.5**), three indicators were found to significantly increase the probability of severe/fatal crashes in a stable manner across all three periods, namely, the central, eastern, and southern parts of the country (the northern part of the country was significant only in 2012–2013). Similarly, the central, northern, and southern parts of country crash were found to be significant in increasing the likelihood of severe/fatal injury in crashes involving non-speeding driving for the 2016–2017 model. Notably, eastern crashes produced unstable effects across time periods by shifting the positive marginal effect on severe/fatal injury in 2014–2015 to a negative one in 2016–2017.

3.8 Limitation and future direction

This study is not without limitations. First, the number of observations of used in each model were considerably small, particularly non-speeding driving crashes models, as compared to sample sized recommended by Ye and Lord (2014) for unobserved heterogeneity modelling approaches, which should be taken into consideration in future study (the use of larger data bases should provide more precise probability estimates). Second, analysing the speeding-related crashes without separating the effect of weather condition may result in bias estimation result. This is because drivers tend to intuitively adjust their behaviour and abilities relative to weather conditions when operating their vehicles, which may make interpreting and comparing crash data analysis between adverse and fine weather conditions laborious and challenging (Theofilatos and Yannis, 2014). This element (separation between exceeding the posted speed limit and driving too fast under adverse weather condition) should also be given consideration for future work. Lastly, as already mentioned in above section, the cause of the observed temporal instability of numerous variables is not entirely clear. However, the general temporal instability found in the current study maybe driven by the result of a subset of observations and that temporal instability maybe existing in some if not most of the observation (Islam and Mannering, 2020). Identifying the stability of observation could be done using a latent class structure with one class identifies crashes where parameter estimates vary over times and another class identifies crashes where parameter fixed over time (Islam and Mannering, 2020; Fountas et al., 2018). Despite potentially computational complexities, this model would be fruitful for future direction to unravel the complexities of temporal instability in crash data.

3.9 Conclusions and Recommendation

Using single-vehicle crash data related to speeding and non-speeding driving in Thailand from 2012 to 2017, this study offered new insights into the factors affecting the driver-injury severity. These estimated models showed a wide variety of risk factors significantly influencing driver-injury severities including driver characteristics, roadway attributes, vehicle type, crash, and environmental, temporal, and spatial characteristics. A random parameters binary logit with heterogeneity in mean and variance approach were employed for model analysis. The result of a series of Likelihood ratio tests indicates statistically significant difference between crashes involving speeding and non-speeding driving, and both speeding and non-speeding driving crash injury severity models exhibited statistically significant temporal instability over the three considered periods. For speeding crash models, while most of the factor showed relatively unstable effect over time, stable factors (significant in all three period models) that decreasing likelihood of severe and fatal injury are restrained driver, van, passenger car, pickup truck, running off road on straight and hitting guardrail and mounting traffic island; whereas stable factor that increasing probability of severe and fatal injury are central, eastern, and southern parts of the country. On the other hand, for non-speeding driving crash model, stable factors that decreasing likelihood of severe and fatal injury are restrained driver, truck, and running off road on straight and hitting guardrail; where stable factors that increasing likelihood of severe and fatal injury are driver under influence of alcohol and van (despite unvarying with respect to the sign, the magnitude of the marginal effects of these factors considerably varies over time). Additionally, notable contradictory effect of several factors between speeding vs. non-speeding driving was also uncovered including older driver, male driver, raised median, two-lane and four-lane roads, road under construction, U-turn, van, raining, unlit and lit roads, and morning peak hour.

Some immediate recommendations to improve safety can obtained. First young driver (subjected to higher risk of fatal injury in latest period), male driver and drivers under influence of alcohol should be targeted with strict law enforcement and emphasized when conducting safety campaign. With stable effect in mitigating severe or fatal injury, related authorities should continually encourage all drivers to use of seatbelt through educational campaign and policy maker should also implement a strict penalty on those who don't equip seatbelt while driving. Similar recommendations were also recently reported from perspective of willingness to pay for accident risk reduction (Jomnonkwao et al., 2021). According to roadway characteristic result, controlling speed limit within road with raised and barrier median, particularly urban area, should be firmly implemented through increasing police check points and speed cameras. Regarding van or minibus of private stakeholder's result, related authorities should regularly check the quality of the vehicle In terms of safety aspect whether they are suitable for providing the service, and penalize those stakeholders who still operates using old vehicle with suitable fine (this may also be generalized to other developing countries other than Thailand). In terms of crash characteristics finding, with stable effect of guardrail in mitigating driver injury severity, road design planner should provide guardrail protection for all curve road section and straight road section where prone to higher risk of run-off-roadway crash. The findings of this research indicates the importance of separating speeding and non-speeding crashes accounting for the temporal instability and unobserved heterogeneity, which could potentially be utilized to improve highway safety and facilitate the development of more effective crash injury mitigation policies, such as organizing targeted campaigns, revising and improving suitable law enforcements and penalties, and continuing to implement the road design that consistently aids in reducing resulting injury severity, by carefully considering the stability or instability of significant factors across time periods and across models.

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CHAPTER IV

THE IMPACT OF WEEKDAY, WEEKEND, AND HOLIDAY CRASHES ON MOTORCYCLIST INJURY SEVERITIES: ACCOUNTING FOR TEMPORAL INFLUENCE WITH UNOBSERVED EFFECT AND INSIGHT FROM OUT-OF-SAMPLE PREDICTION

4.1 Abstract

This paper examines the differences between weekday, weekend, and holiday crashes on the severity of motorcyclist injury using four-year motorcycle crash data in Thailand from 2016-2019. While also considering the temporal stability assessment of significant factors, this study adopted a random parameters logit model with possible heterogeneity in means and variances to account for unobserved heterogeneity. Three levels of motorcyclist injury severity were considered including minor injury, severe injury, and fatal injury. Two series of likelihood ratio tests clearly indicated nontransferability between weekday, weekend, and holiday crashes and substantial temporal instability over the four-year study period. Findings also revealed many statistically significant factors that affect motorcyclist injury severity probabilities in various time-of-year and yearly models. In addition, the prediction comparison results (using out-of-sample prediction simulation) clearly illustrated substantial differences between weekday, weekend, and holiday motorcyclist injury severity probabilities, and substantial changes in each injury predicted probabilities over time. This paper highlights the importance of accounting for day-of-week and holiday transferability and temporal instability with unobserved effects in determinants that affect motorcyclist injury severity. Through nontransferability and temporal instability, the findings provide valuable knowledge for practitioners, researchers, institutions, and decision-makers to enhance highway safety, specifically motorcyclist safety, and facilitate the development of more effective motorcycle crash injury mitigation policies.

4.2 Introduction

As widely recognized then and now, motorcycle crashes account for the majority of severe injuries and fatalities due to motorcyclists' lack of protection compared to other types of vehicle driver (e.g., passenger car, bus, van, truck, etc.). According to a 2015 World Health Organization report, the motorcyclist fatality rate makes up approximately one-fourth of the global roadway crash fatality rate, while populations in low- and middle-income developing countries are at higher risk compared with the developed countries (WHO, 2015). In Thailand, for example, motorcyclists were involved in about 74% of the total road crash fatality rate in 2016 (WHO, 2018). In comparison, the motorcyclist fatality distribution increased by 5.5% in 2019, while there was also a significant increase in the number of motorcycle crashes and motorcyclist fatalities (Se et al., 2021a). It should be noted that this serious issue contributes not only to the social emotional burden but also to the economics of the country. In Thailand, at the end of 2017, the total productivity loss due to road traffic crashes alone was approximately 121 billion Baht (45 billion Baht from fatalities, 7 billion Baht from disabilities, 67.5 billion Baht from serious injuries, and 1.5 billion Baht from slight injuries), which is nearly 0.8% of the country's gross domestic product (Chantith et al., 2021). This exacerbated trend has become a serious safety concern and gained more attention from both researchers and practitioner agencies.

From a weekly perspective, traffic and human characteristics may vary by day-of-week (i.e., weekdays and weekends), which may further influence the effect of explanatory variables on injury severity outcomes. The differences between weekend and weekday crashes could be attributed to the diverse driver behaviors of weekday and weekend travelers. Additionally, unobserved factors associated with traffic volume, travel intention/direction, ambient behaviors, and so on may potentially differ across day-of-week (Alnawmasi and Mannering, 2019; Behnood and Al-Bdairi, 2020). In fact, scholars have shown significant variations in factors affecting injury severity arising from differences between weekday and weekend crashes. Using day-of-week segmentation data, many studies have provided more insights into the differences between weekday and weekend crash injury severities (e.g., single-vehicle crashes (Adanu et al., 2018), pedestrian–vehicle crashes with temporal influence (Li et al., 2021c), alcohol-impaired driving crashes with temporal influence (Yan et al., 2021a), and large-truck crashes (Behnood and Al-Bdairi, 2020)). These studies strongly suggest conducting crash-injury severity analysis separately by day-of-week. However, other critical times-of-year are holiday festive periods, which could also significantly influence changes in traffic characteristics and human behaviors from the normal day-of-week period. Despite being a period of enjoyment and festivity, it is undeniable that the holiday seasons bring not only happiness but also sadness with losses. Holiday periods witness an increase in partying, drunkenness, speeding, reckless driving behaviors, and number of travels with longer trip distances and travels on unfamiliar roadway environments (Anowar et al., 2013; Se et al., 2020a). Compared to weekdays and regular weekends, holidays' travel models, trip chain choices, and travel behaviors are significantly different as proven by research (Wang et al., 2015; Yang et al., 2016). During holiday periods, not only the road traffic volume increases but also roadway crashes as well as the rate of fatality and serious injury (Anowar et al., 2012). Likewise, in Thailand context, as shown in **Figure 4.1**, during the months of two important holidays (Western New Year [late December and early January] and the Songkran festival [mid-April]), the number of motorcycle crashes remarkably jumps to its peak in April followed by December and January, while the frequency of motorcycle crashes in the other months remained low and approximately the same. Examining the injury severity distribution (**Figure 4.2**), however, the percentage of minor and severe injuries in holiday crashes is significantly higher even though the fatal injury distribution is relatively lower than in weekend and weekday crashes. Temporally speaking, the fatality distribution for weekday and holiday crashes gradually rose whereas the severe injury distribution observably fluctuated. Both fatality and severe injury distributions for weekend crashes also temporally fluctuated. Notably, weekend crashes have the highest fatality distribution percentage (slightly higher than weekday crashes) whereas holiday crashes have the highest severe injury distribution percentage. Such circumstances signal a need to conduct research on motorcyclist injury severity by separately considering holidays, weekdays, and weekends.

In the last several years, global interest in crash injury severity research has clearly been on the temporal instability investigation of significant risk factors (i.e., the change in the effect of explanatory variables over time) and the need to account for unobserved heterogeneity. Mannering (2018) provided a detailed review of the reasons that may play significant roles in temporal instability regarding the effect of explanatory variables on the resulting injury severities. Whereas, Mannering et al. (2016) offered a robust review of the potential reasons that may cause unobserved heterogeneity for both crash rate and crash injury severity research and review of the methodological approaches that can be utilized to deal with it. Numerous recent works have accounted for both aspects in their respective injury severity models (Alnawmasi and Mannering, 2019; Alogaili and Mannering, 2022; Behnood and Mannering, 2019; Behnood and Mannering, 2015; Fanyu et al., 2021; Hou et al., 2022; Islam et al., 2020; Islam and Mannering, 2020; Li et al., 2021c; Se et al., 2021b; Yan et al., 2021a, 2021b, 2021c; Yu et al., 2019; Yu et al., 2020, 2021; Zamani et al., 2021). These aforementioned studies have collected substantial evidence that ignoring temporal influence and unobserved heterogeneity in roadway crash injury severity research would indeed result in bias and unreliable results and conclusions.

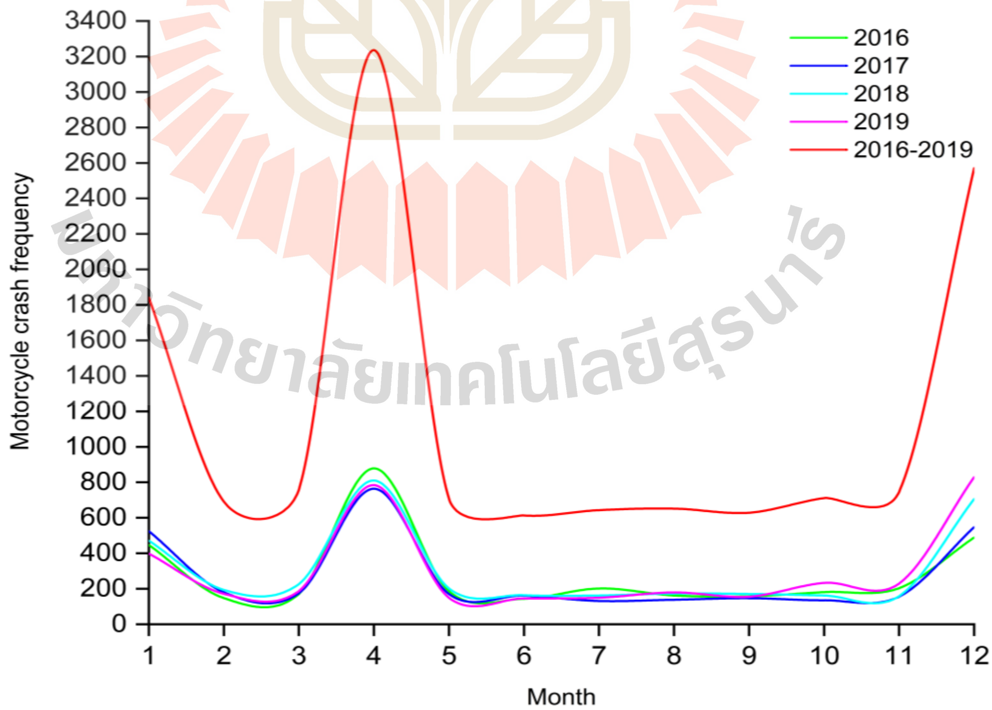

Figure 4.1 Monthly motorcycle crash frequency by year from 2016–2019 in Thailand

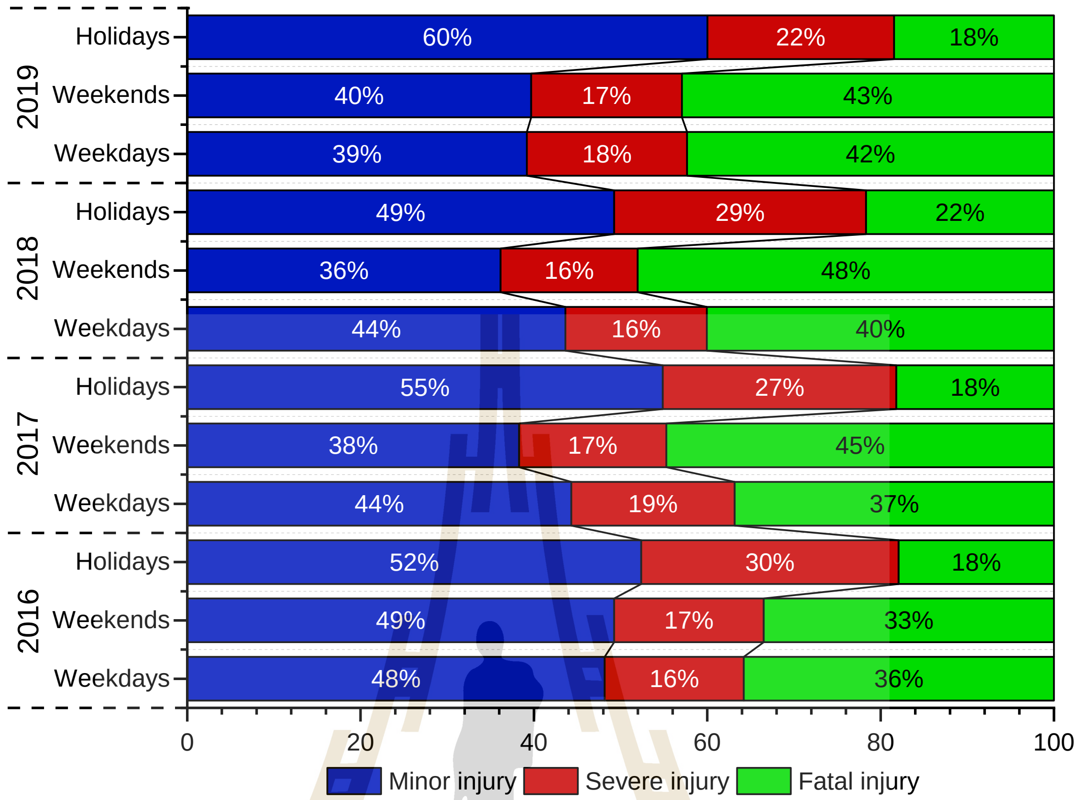

Figure 4.2 Motorcyclist injury severity distribution of weekdays, weekends and holidays crashes over the years: 2016–2019

Alongside temporal instability investigations, some of the abovementioned studies compared between two or more groups of datasets (e.g., time-of-day, day-of-week, genders, driving behaviors, etc.). However, most of these studies have ignored insights into a clearer picture of the differences between each segmentation data (either by group or by year of data), which can possibly be obtained using an out-of-sample prediction simulation. This out-of-sample prediction was extensively demonstrated and discussed by Hou et al. (2022). From an injury severity research perspective, Alogaili and Mannering (2020) applied a full out-of-sample prediction simulation using the driver-estimated model of one model to predict the other model while controlling the crash characteristics of the observed model, to better understand the difference between Saudi and non-Saudi driver-injury severity outcomes. The same out-of-sample prediction simulation assessment was also applied by Islam et al. (2020) (to determine the injury severity distribution of work zone crashes in 2017 using a 2012 model estimate and compared with the observed 2017 injury severity distribution), Alogaili and Mannering (2022) (to see the extent of injury severity distribution of nighttime vehicle-pedestrian crashes using daytime crashes model estimate), and Alnawmasi and Mannering (2022) (to examine the injury severity distribution of crashes after the speed limit was raised from 70 to 75 mph using model estimate of the crashes before the speed limit was implemented). This application of the out-of-sample prediction simulation could provide a clearer picture of the changes in injury severity distribution between models as well as important insights into the aggregate impact of effect differences (either data segmentation or yearly data).

In the context of motorcycle crash research, only a few scholars have extensively considered the temporal influence in motorcyclist injury severity study. For example, mainly focusing on policy recommendations, Alnawmasi and Mannering (2019) found that a new rider gaining experience, changes in motorcycle technology/performance, changes in macroeconomic conditions, changes induced by how a rider responds to the changing behavior of other road users, and changes in riders' behavior and skill over time may play important roles in the temporal instability of factors affecting motorcyclist injury severities. Although focusing on a comparison between two heterogeneity approaches (latent class clustering and latent segmentation–based models), Chang et al. (2022) also found a great temporal instability in the marginal effect of risk factors on motorcyclist injury severity level. With a primary focus on motorcyclist safety policy evaluation, the purpose of the current study is novel, as it specifically focuses on the temporal instability of the contributing factors using different angles from the previous work: (1) It uses data from a developing country (Thailand), where motorcycles represent the majority of registered vehicles, and uses different sets of observation and additional explanatory variables that may feature specific parameter distributions as a result of varying levels of motorcyclist injury severities. (2) It explores the differences between weekday, weekend, and holiday motorcyclist injury severities alongside a temporal instability investigation and an accounting for unobserved heterogeneity. (3) Besides interpreting and investigating temporal instability based on a summary of average marginal effects of significant explanatory variables, the current study extensively conducts a series of out-of-sample prediction simulations to better understand the changes in motorcyclist injury severity distributions across time-of-year and yearly models.

This study begins by reviewing the methodological approaches and findings of previous studies on motorcyclist injury severity. The paper then describes the selected methodology and data collection followed by transferability and temporal stability tests. The model results are then discussed, followed by insights offered by the out-of-sample prediction simulations. Finally, the paper concludes and summarizes the results.

4.3 Literature review

Table 4.1 summarizes motorcyclist injury severity studies by year of publication. It shows that the studies have employed different econometric and statistical techniques to explore factors that influence motorcyclist injury severity, starting from a standard discrete choice model to a sophisticated heterogeneity model such as various extensions of latent class models and random parameter models. As shown in **Table 4.1**, scholars have explored a wide range of significant risk factors such as rider characteristics and actions (e.g., gender, age, pillion rider, alcohol consumption, speeding, helmet usage, etc.), roadway characteristics (e.g., curve roads, roads on grade, intersections, U-turns, traffic control systems, speed limits, etc.), motorcycle characteristics (e.g., age of motorcycle and engine size), crash characteristics (e.g., hitting a specific type of vehicle, hitting pedestrians, hitting bicyclists, hitting fixed objects, angle crashes, side-swipe crashes, head-on crashes, rear-end crashes, etc.), temporal and environmental characteristics (e.g., dry surface, wet surface, rain, peak hours, nighttime with/without lighting, daytime, etc.), and spatial characteristics (e.g., rural, urban, residential, etc.).

Notably, there are several broad agreements among the findings of the previous studies. However, there are also some conflicting findings (e.g., the effect of gender, pillions, and lighting conditions when the crashes occurred). Although some factors have the same influence on resulting injury severity across different studies, the magnitudes of the effects observably vary. Alnawmasi and Mannering (2019) identified several reasons for this instability including the use of different methodological approaches,

Table 4.1 A summary of the past motorcyclist-injury severity studies

Authors	Methodology	Location	Key findings
Zambon and Hasselberg (2006)	Univariate and multivariate stepwise logistic regression.	Sweden	*Increasing the likelihoods of severer injury:* alcohol consumption, driving in a rural area, posted speed limit over 50 km/h, and single-motorcycle crashes. *Decreasing the likelihoods of severer injury:* sunny, female, and daylight.
De Lapparent (2006)	Empirical Bayesian method based on the Multinomial-Dirichlet model	France	*Increasing the likelihoods of severer injury:* hitting public transportation, hitting automobile, and large engine size. *Decreasing the likelihoods of severer injury:* hitting pedestrian, hitting bicycle, hitting motorcycle, and daylight.
Savolainen and Mannering (2007)	Nested logit model and Multinomial logit model	Indiana, USA	*Increasing the likelihoods of severer injury:* increasing motorcyclist age, alcohol consumption, pillion, unsafe speed, darkness, run-off-road, and hitting various fixed objects. *Decreasing the likelihoods of severer injury:* motorcycle age less than 5 years, helmet used, wet pavement, and crash at intersection.

Table 4.1 A summary of the past motorcyclist-injury severity studies (Cont.)

Authors	Methodology	Location	Key findings
Albalate and Fernández-Villadangos (2010)	Ordered logistic regression model	Barcelona, Spain	*Increasing the likelihoods of severer injury:* male, excess speed, road width, and alcohol consumption. *Decreasing the likelihoods of severer injury:* congestion traffic conditions.
Schneider and Savolainen (2011)	Multinomial logit model	Ohio, USA	*Increasing the likelihoods of severer injury:* high speed, alcohol consumption, collisions with fixed objects, and high-impact crashes (angle and head-on collisions). *Decreasing the likelihoods of severer injury:* Helmet use offered most promising means of reducing severe and fatal injuries in both single- and multivehicle crashes.
Geedipally et al. (2011)	Multinomial logit model	Texas, USA	*Increasing the likelihoods of severer injury:* alcohol, female, old rider, presence of both horizontal and vertical curves, good pavement condition, single-motorcycle crash, and angular crashes. *Decreasing the likelihoods of severer injury:* young rider, lighting, helmet used, same direction crash, intersection related-crash, and divided highways.

Table 4.1 A summary of the past motorcyclist-injury severity studies (Cont.)

Authors	Methodology	Location	Key findings
Rifaat et al. (2012)	Ordered logit model, Heterogeneous choice model, and Generalized ordered logit model	Calgary, Canada	*Increasing the likelihoods of severer injury:* neighborhoods with loops and lollipops types of streets, right-angle crashes, left-turn-across-path crashes, hitting a truck, unsafe speed, and alcohol use. *Decreasing the likelihoods of severer injury:* parking lots, during winter, hitting a van, male rider, and rider following-too-closely to the vehicle in front.
Shaheed et al. (2013)	RPL models	Iowa, USA	*Increasing the likelihoods of severer injury:* angle crash, non-motorcycle drivers' vision not obscured, speed limit greater than 55 mph, dry road surface, hitting pick-up truck, non-MC driver failed to yield at stop sign, hitting van/minivan/SUV turning left, and male rider. *Decreasing the likelihoods of severer injury:* daylight condition, helmet used, hitting passenger car, and urban area.

Table 4.1 A summary of the past motorcyclist-injury severity studies (Cont.)

Authors	Methodology	Location	Key findings
Jung et al. (2013)	Multinomial logit model	California, USA	*Increasing the likelihoods of severer injury:* lack or improper use of helmets, victim ejection, alcohol/drug effects, collisions (head-on, broadside, hit-object), hitting a truck, weekend and non-peak hour activity (young and old rider), movement of running off the road preceding a collision and multi-vehicle involvement (old riders), at-fault driver, local road, and speed violation (young rider). *Decreasing the likelihoods of severer injury:* Use of street lights in the dark, side-swipe, rear-end, and female.
Kashani et al. (2014)	Classification and Regression Trees (CART)	Iran	*Increasing the likelihoods of severer injury:* pillion rider, rural area, and head and neck injury. *Decreasing the likelihoods of severer injury:* helmet usage.
Shaheed and Gkritza (2014)	Latent class multinomial logit model	Iowa, USA	*Increasing the likelihoods of severer injury:* speeding, run-off-road, hitting fixed object, over turn crash, rural area, weekend, and drug or alcohol used. *Decreasing the likelihoods of severer injury:* unlit road, young rider, and helmet used.

Table 4.1 A summary of the past motorcyclist-injury severity studies (Cont.)

Authors	Methodology	Location	Key findings
Chang et al. (2016)	Mixed Ordered Logit Approach	Hunan, China	*Increasing the likelihoods of severer injury:* motorcycle riders older than 60 years, the absence of helmets, motorcycle riders identified to be equal duty, motorcycle colliding with a heavy vehicle during the night time without lighting, curve, and slope alignment. *Decreasing the likelihoods of severer injury:* unsignalized intersections and daylight.
Islam and Brown (2017)	Random parameter logit models	Alabama, USA	*Increasing the likelihoods of severer injury:* clear weather, unlit road, old female rider, freeway, horizontal curve, evening period, under influence of alcohol, and non-helmet used. *Decreasing the likelihoods of severer injury:* young riders, residential area, and intersection.
Xin et al. (2017)	Mixed-effects logistic model	Florida, USA	*Increasing the likelihoods of severer injury:* sharp curves (radius <1,500 ft), speeding over 50 mph/over speeding limit, dry road surface, darkness with/without lighting, hitting fixed object, alcohol used, weekend, and old rider. *Decreasing the likelihoods of severer injury:* helmet used, young rider, poor pavement condition, and existing auxiliary lane.

Table 4.1 A summary of the past motorcyclist-injury severity studies (Cont.)

Authors	Methodology	Location	Key findings
Waseem et al. (2019)	RPL with heterogeneity in means and variances	Pakistan	*Increasing the likelihoods of severer injury:* involving middle-aged riders (25–50 years) and riders with no education, occurring on roads with posted speed limit of 70 kms per hour or higher, crashes involving a motorcycle and a heavy vehicle, involving collision of a motorcycle with a fixed object, and crashes occurring during dry weather conditions. *Decreasing the likelihoods of severer injury:* occurring on divided streets and road segments with a posted speed limit of less than 50 kms per hour, involving Chinese brand motorcycles, involving registered motorcycles, and where at least one motorcycle and auto rickshaw is involved.
Wahab and Jiang (2019)	Multinomial logit model	Ghana	*Increasing the likelihoods of severer injury:* At a junction, weekend, signage, poor road shoulder, village settlement, tarred and good road surface, and collision between motorcycle and heavy goods vehicle (HGV). *Decreasing the likelihoods of severer injury:* motorcycle crashes occurring during the daytime, in curves or inclined portions of roads, or in unclear weather conditions.

Table 4.1 A summary of the past motorcyclist-injury severity studies (Cont.)

Authors	Methodology	Location	Key findings
Alnawmasi and Mannering (2019)	RPL with heterogeneity in means and variances	Florida, USA	*Increasing the likelihoods of severer injury:* old rider, under influence of alcohol or drug, darkness, dry road surface, exceeding speeding limit, vertical grade, friction larger than 45, pave shoulder and speed more than 50 mph. *Decreasing the likelihoods of severer injury:* daylight, clear weather, and helmet usage.
Vajari et al. (2020)	Multinomial logit model	Victoria, Australia	*Increasing the likelihoods of severer injury:* motorcyclists aged over 59 years, weekend crashes, midnight/early morning crashes, morning rush hours crashes, multiple vehicles involved in the crash, T-intersections, crashes in towns, crashes in rural areas, stop or give-way intersections, roundabouts, and uncontrolled intersections. *Decreasing the likelihoods of severer injury:* female motorcyclists, snowy or stormy or foggy weather, rainy weather, evening rush hours crashes, and unpaved roads.

Table 4.1 A summary of the past motorcyclist-injury severity studies (Cont.)

Authors	Methodology	Location	Key findings
Li et al. (2021a)	Latent Class Ordered Probit Model	California, USA	*Increasing the likelihoods of severer injury:* pre-speed, permanent physical impairments, low temperature, bad lighting condition, and hitting a truck. *Decreasing the likelihoods of severer injury:* junction and divided trafficway.
Ijaz et al. (2021)	RPL with heterogeneity in means and variances	Pakistan	*Increasing the likelihoods of severer injury:* crashes occurred during weekdays, involving riders aged above 50 years, involving the collision of motorcycles with passenger car and heavy vehicles, involving a female as a pillion rider, and those that occurred due to over speeding. *Decreasing the likelihoods of severer injury:* cloudy weather, rainy weather, off-peak hour, daylight, wrong turning, and U-turn area.
Li et al. (2021b)	Geographically-Temporally Weighted Ordered Logistic Regression	Pennsylvania, USA	*Increasing the likelihoods of severer injury:* exceeding speed limit, hitting truck, head-on, angle crash, hitting animal, impaired rider, male rider, increasing engine size, downhill, curve road, and rural area. *Decreasing the likelihoods of severer injury:* rear-end crash, helmet usage, pillion rider, dark with light, and raining.

Table 4.1 A summary of the past motorcyclist-injury severity studies (Cont.)

Authors	Methodology	Location	Key findings
Islam (2021)	RPL with heterogeneity in means and variances	Florida, USA	*Increasing the likelihoods of severer injury:* hitting fixed object, curve road, urban principal arterial, darkness, and midnight to early morning. *Decreasing the likelihoods of severer injury:* young rider, ejection, rider only, and daylight.
Sivasankaran et al. (2021)	Ordered logit model	Tamil Nādu, India	*Increasing the likelihoods of severer injury:* motorcyclists hit stationary fixed objects, hit trees, ran-off road, inclement weather conditions, and urban areas. *Decreasing the likelihoods of severer injury:* single and two-lane roads, highways, village roads, district roads, daylight conditions, drivers who are younger and working-age group, overtaking from left, and taking U-turn.
Chang et al. (2021)	Latent class clustering and latent segmentation-based models	Queensland, Australia	*Increasing the likelihoods of severer injury:* high-speed limit, hit stationary objects, head-on, angular crashes, dim light, and unlicensed riders. *Decreasing the likelihoods of severer injury:* rider's age between 25 and 44, and at-fault riders.

different sample sizes (those with low observations of crash data could suffer from omitted-variable bias), different locations of data collection, and, more importantly, different periods of data collection. In addition to what was discussed in the Introduction section, these reasons could also potentially differentiate the current paper from the previous studies.

4.4 Methodology

Regarding empirical settings in injury severity research, analysts cannot collect all crash-level factors associated with the crash injury severity outcomes, which may be derived from physiological differences between genders, physical characteristics of occupants with different/same age, variability in the effect of passengers in the vehicle, variability in roadway attributes, vehicle features, or even weather and environmental characteristics. Such unavailable attributes constitute a so-called unobserved characteristics or unobserved heterogeneities, which require a careful consideration to obtain nonbiased, reliable, and consistent estimation results (Mannering and Bhat, 2014; Mannering et al., 2016). To address this issue, researchers have introduced various unordered and ordered heterogeneity modeling approaches into crash injury severity studies, including random parameters (mixed) logit model (Kim et al., 2013; Li et al., 2019), random parameters ordered logit/probit model (Azimi et al., 2020; Mokhtarimousavi et al., 2020), latent class multinomial logit model (Behnood et al., 2014; Liu and Fan, 2020), latent class ordered logit/probit model (Fountas et al., 2018; Yasmin et al., 2014), random parameters model with heterogeneity in means (and variances) (Behnood and Mannering, 2017; Seraneeprakarn et al., 2017; Se et al., 2022a, 2022b), random parameters ordered model with heterogeneity in means (and variances) (Xin et al., 2017a; Yu et al., 2020), correlated random parameter model (with heterogeneity in means) (Ahmed et al., 2021; Fountas et al., 2021; Se et al., 2021a, 2021b; Wang et al., 2021), and random threshold random parameters hierarchical ordered probit model (Fountas and Anastasopoulos, 2017; Yu et al., 2021). However, the selection process between the unordered and ordered probability heterogeneity models may be a tedious task, since both approaches share benefits and limitations (Fountas and Anastasopoulos, 2017). However, past study argued that crash injury severity research requires a framework that can account for the natural order of severity level (e.g., from no injury to minor injury to severe injury and to fatal injury) and the unobserved heterogeneity inherent in the effect of crash-level factors and severity levels (Song and Fan, 2020). Other studies (Hou et al., 2021; Islam and Mannering, 2021) asserted that the random parameters logit model which allows for possible heterogeneity in means and variances could provide the great flexibility in capturing a greater extent of underlying unobserved characteristics, more precise predictions, and better model fit. Considering three levels of motorcyclist injury severity outcomes—minor injury, severe injury and fatal injury—this study extensively considered the random parameters logit model with heterogeneity in means and variances.

The modeling begins by defining a function that determines motorcyclist injury severity as follows (Washington et al., 2020):

$$Y_{nm} = \beta_n \boldsymbol{X}_{nm} + \varepsilon_{mn} \tag{4.1}$$

where Y_{nm} represents the injury severities function of motorcyclist injury severity outcome *n* involved in motorcycle crash *m*. β_n and $\boldsymbol{X}_{nm}$ denote vectors of estimable parameters and vectors of various crash-level factors that affect motorcyclist injury severity, respectively, whereas ε_{mn} is an error term. To eliminate possible erroneous or biased results due to unobserved characteristics, parameter estimates were allowed to vary across crash observations, which can be written as follows (Train, 2009; Washington et al., 2020):

$$P_m(n) = \int \frac{EXP(\beta_n \boldsymbol{X}_{nm})}{\sum_{\forall n} EXP(\beta_n \boldsymbol{X}_{nm})} f(\beta_n|\varphi_n) d\beta_n \tag{4.2}$$

where $P_m(n)$ is the probability that a motorcyclist in crash *m* will sustain injury severity outcome *n* (i.e., set of three possible injury severity outcomes), $f(\beta_n|\varphi_n)$ refers to the density function of β_n and φ_n denotes a vector of parameters describing the density function (mean and variance), and all other terms are previously defined. Various types of density function were empirically tested including standard normal, triangular, standard uniform and lognormal distribution. However, normal distribution was found to provide the best statistical fit compared to all others.

A greater depth of accounting for unobserved heterogeneity is to allow the means and variances of random parameters to be influenced by other crash-level factors. This can be done by letting β_{nm} be a vector of estimable parameters that vary across crashes, which can be derived as follows (Seraneeprakarn et al., 2017; Washington et al., 2020):

$$\boldsymbol{\beta}_{nm} = \beta_n + \boldsymbol{\delta}_{nm}\boldsymbol{Z}_{nm} + \sigma_{nm}EXP(\boldsymbol{\omega}_{nm}W_{nm})\upsilon_{nm}, \tag{4.3}$$

where $\boldsymbol{Z}_{nm}$ represents a vector of attributes that capture heterogeneity in means that influence motorcyclist injury severity level *n*, $\boldsymbol{\delta}_{nm}$ is the corresponding vector of estimable parameters. W_{nm} is a vector of attributes that capture heterogeneity in standard deviation σ_{nm} with corresponding parameter vector $\boldsymbol{\omega}_{nm}$, and υ_{nm} denotes a disturbance term. During the estimation process, the model was estimated by a simulated maximum likelihood with 1,000 Halton draws which should be sufficient to generate consistent and reliable results (Alogaili and Mannering, 2022; Islam et al., 2020; Se et al., 2021b; Seraneeprakarn et al., 2017).

To facilitate the interpretation of the model findings, average marginal effects over all crash observations were also computed to determine the effect of a one-unit change in any specific explanatory variable on the probability of an injury severity outcome (i.e., since this study used only indicator variables, the marginal effect is the change in probability resulting from the indicator going from 0 to 1). The average marginal effects of the indicator variables can be computed as follows (Hou et al., 2022; Song et al., 2021):

$$ME_{X_{mi}}^{P_m} = \frac{1}{i}\sum_{m=1}^{i}[P_m(X_{mi} = 1) - P_m(X_{mi} = 0)] \tag{4.4}$$

where the average difference value of P_m over all observations is calculated when the *i*-th explanatory variable X_{mi} changes from 0 to 1.

4.5 Empirical Setting

This study used four years of police-reported motorcycle crash data from January 1, 2016, to December 31, 2019, that collected from all highways under the control of the Department of Highways (DOH). The motorcycle crash data were filtered from the Highways Accident Information Management System (HAIMS), DOH. The data comprise a total of 13,422 motorcycle crashes. This study defined subsets of data as follow:

– Weekday data: crashes occurred between Monday and Friday (excluding the days overlapping with Western New Year and Songkran festival)

– Weekend data: crashes occurred between Saturday and Sunday (excluding the days overlapping with Western New Year and Songkran festival)

– Holiday data (major/long holidays): Crashes occurred during Western New Year and Songkran festival.

Detailed information on the explanatory variables were categorized into four groups: rider characteristics and actions (e.g., gender, pillion, speeding, hitting unexpected objects, improper overtaking, under the influence of alcohol, and fatigue), roadway attributes (e.g., main lane, frontage lane, work zone, number of lanes, median type, pavement type, alignment, intersection, U-turn, bridge, and urban or rural), environmental and temporal characteristics (e.g., wet road, lit or unlit road, and various times of the day), and crash types and characteristics (such as hitting a specific type of vehicle, rear-end type, side-swipe type, single-crash type, and head-on type). The following statistical analysis considered three levels of motorcyclist injury severity: minor, severe, and fatal injury. **Table 4.2** presents the frequency of observed resulting injury severity of motorcyclists and the summary of descriptive statistics of the explanatory variables for each time-of-year model from 2016 to 2019.

4.6 Transferability and Temporal Stability Testing

Many recent studies have justified that the impacts of factors influencing the resulting-injury severity of crashes have changed over time. These injury severity studies include single-vehicle crashes (Behnood and Mannering, 2015; Islam and Mannering, 2020;

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency

	2016			**2017**		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Rider-injury severity (Frequency)						
Minor	708	303	506	658	185	682
Severe	236	106	287	280	82	335
Fatal	526	206	173	547	216	226
Total	1470	615	966	1485	483	1243
Explanatory variables	Mean	Mean	Mean	Mean	Mean	Mean
	(Std)	(Std)	(Std)	(Std)	(Std)	(Std)
Rider characteristic/actions						
Male (1 if rider was male, 0 female)	0.789	0.829	0.784	0.795	0.821	0.768
	(0.407)	(0.376)	(0.411)	(0.403)	(0.382)	(0.422)
Pillion (1 if there was/were pillion(s), 0 otherwise)	0.362	0.341	0.302	0.332	0.356	0.277
	(0.480)	(0.474)	(0.459)	(0.471)	(0.479)	(0.447)
Speeding (1 if rider was speeding, 0 otherwise)	0.714	0.733	0.561	0.657	0.714	0.534
	(0.451)	(0.442)	(0.496)	(0.474)	(0.452)	(0.499)
Hit unexpected crossing object (1 if rider hit a unexpected crossing object, 0 otherwise)	0.202	0.178	0.253	0.243	0.192	0.255
	(0.401)	(0.383)	(0.435)	(0.429)	(0.394)	(0.436)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2016			2017		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Overtake (1 if rider overtook improperly, 0 otherwise)	0.014	0.021	0.012	0.011	0.012	0.018
	(0.118)	(0.143)	(0.110)	(0.106)	(0.110)	(0.134)
Alcohol (1 if rider was under influence of alcohol, 0 otherwise)	0.009	0.008	0.105	0.018	0.010	0.110
	(0.097)	(0.089)	(0.307)	(0.133)	(0.101)	(0.313)
Fatigued (1 if rider was fatigued, 0 otherwise)	0.005	0.004	0.008	0.010	0.004	0.012
	(0.073)	(0.069)	(0.090)	(0.103)	(0.064)	(0.109)
Roadways attributes						
Main lane (1 if crash occurred on main lane, 0 otherwise)	0.061	0.055	0.023	0.070	0.086	0.037
	(0.239)	(0.228)	(0.152)	(0.255)	(0.282)	(0.188)
Frontage lane (1 if crash occurred on frontage lane, 0 otherwise)	0.082	0.082	0.014	0.086	0.095	0.012
	(0.275)	(0.275)	(0.119)	(0.280)	(0.293)	(0.109)
Work zone (1 if crash occurred on work zone, 0 otherwise)	0.035	0.034	0.020	0.018	0.026	0.016
	(0.184)	(0.181)	(0.142)	(0.133)	(0.162)	(0.125)
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise)	0.402	0.386	0.401	0.424	0.366	0.428
	(0.490)	(0.487)	(0.490)	(0.494)	(0.482)	(0.495)
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise)	0.267	0.302	0.442	0.280	0.308	0.412
	(0.442)	(0.459)	(0.496)	(0.449)	(0.462)	(0.492)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2016			2017		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Undivided median (1 if crash occurred on undivided road, 0 otherwise)	0.335	0.354	0.549	0.350	0.362	0.486
	(0.472)	(0.478)	(0.497)	(0.477)	(0.481)	(0.500)
Flush median (1 if crash occurred on flush median road, 0 otherwise)	0.073	0.063	0.067	0.111	0.093	0.101
	(0.260)	(0.243)	(0.250)	(0.314)	(0.290)	(0.301)
Raised median (1 if crash occurred on raised median road, 0 otherwise)	0.224	0.250	0.195	0.216	0.202	0.214
	(0.417)	(0.433)	(0.396)	(0.411)	(0.402)	(0.410)
Depressed median (1 if crash occurred on depressed median road, 0 otherwise)	0.193	0.164	0.132	0.165	0.180	0.149
	(0.395)	(0.370)	(0.339)	(0.371)	(0.384)	(0.356)
Barrier median (1 if crash occurred on barrier median road, 0 otherwise)	0.167	0.162	0.040	0.151	0.157	0.036
	(0.373)	(0.369)	(0.196)	(0.358)	(0.364)	(0.186)
Concrete pavement (1 if crash occurred on concrete pavement road, 0 otherwise)	0.124	0.123	0.093	0.099	0.113	0.096
	(0.330)	(0.329)	(0.290)	(0.299)	(0.317)	(0.295)
Curve (1 if crash occurred on curve road, 0 otherwise)	0.077	0.094	0.136	0.111	0.115	0.112
	(0.267)	(0.292)	(0.343)	(0.314)	(0.320)	(0.316)
Grade (1 if crash occurred on graded road, 0 otherwise)	0.021	0.024	0.039	0.033	0.033	0.025
	(0.145)	(0.154)	(0.194)	(0.180)	(0.179)	(0.158)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2016			2017		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Intersection (1 if crash occurred within 100m from intersection, 0 otherwise)	0.119	0.126	0.133	0.133	0.113	0.118
	(0.324)	(0.333)	(0.340)	(0.340)	(0.317)	(0.323)
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise)	0.088	0.066	0.063	0.099	0.097	0.076
	(0.284)	(0.249)	(0.243)	(0.299)	(0.296)	(0.265)
Bridge (1 if crash occurred on the bridge, 0 otherwise)	0.014	0.019	0.009	0.010	0.010	0.007
	(0.121)	(0.138)	(0.096)	(0.100)	(0.101)	(0.084)
Urban (1 if crash occurred in urban road, 0 rural)	0.276	0.271	0.170	0.233	0.194	0.164
	(0.447)	(0.445)	(0.376)	(0.423)	(0.396)	(0.370)
Environmental and temporal characteristics						
Wet road (1 if crash occurred on wet road, 0 otherwise)	0.042	0.039	0.011	0.063	0.062	0.064
	(0.201)	(0.193)	(0.106)	(0.244)	(0.241)	(0.245)
Rain (1 if crash occurred under rainy condition, 0 otherwise)	0.043	0.037	0.031	0.071	0.072	0.068
	(0.204)	(0.189)	(0.196)	(0.257)	(0.259)	(0.252)
Lit road (1 if crash occurred on lit road, 0 otherwise)	0.305	0.312	0.236	0.280	0.327	0.263
	(0.460)	(0.463)	(0.424)	(0.449)	(0.469)	(0.440)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2016			2017		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	
Unlit road (1 if crash occurred on unlit road, 0 otherwise)	0.089	0.104	0.132	0.101	0.107	0.143
	(0.285)	(0.305)	(0.339)	(0.301)	(0.310)	(0.350)
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise)	0.112	0.130	0.101	0.124	0.151	0.117
	(0.315)	(0.336)	(0.302)	(0.330)	(0.358)	(0.322)
Peak hours (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise)	0.257	0.214	0.234	0.244	0.207	0.222
	(0.437)	(0.410)	(0.424)	(0.429)	(0.405)	(0.415)
Evening (1 if crash occurred between 18:00-23:59, 0 otherwise)	0.316	0.305	0.290	0.290	0.320	0.315
	(0.465)	(0.461)	(0.454)	(0.454)	(0.467)	(0.464)
Crash characteristics						
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise)	0.136	0.126	0.109	0.115	0.103	0.121
	(0.342)	(0.333)	(0.312)	(0.319)	(0.304)	(0.326)
Hit passenger car (1 if rider hit passenger car, 0 otherwise)	0.329	0.317	0.236	0.292	0.277	0.211
	(0.470)	(0.465)	(0.424)	(0.455)	(0.448)	(0.408)
Hit pickup truck (1 if rider hit pickup truck,0 otherwise)	0.249	0.248	0.250	0.270	0.258	0.252
	(0.432)	(0.432)	(0.433)	(0.444)	(0.438)	(0.434)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2016			2017		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise)	0.062	0.056	0.039	0.058	0.076	0.036
	(0.242)	(0.231)	(0.194)	(0.234)	(0.266)	(0.186)
Hit truck (1 if rider hit large truck, 0 otherwise)	0.128	0.125	0.025	0.142	0.128	0.034
	(0.334)	(0.331)	(0.158)	(0.349)	(0.334)	(0.182)
Rear-end (1 if type was rear-end crash, 0 otherwise)	0.387	0.386	0.267	0.382	0.383	0.278
	(0.487)	(0.487)	(0.442)	(0.486)	(0.486)	(0.448)
Side-swipe (1 if type was side-swipe crash, 0 otherwise)	0.225	0.213	0.221	0.226	0.184	0.207
	(0.418)	(0.409)	(0.415)	(0.418)	(0.388)	(0.405)
Single-crash (1 if type was single-crash crash, 0 otherwise)	0.135	0.147	0.292	0.162	0.198	0.259
	(0.342)	(0.355)	(0.455)	(0.368)	(0.399)	(0.438)
Head-on (1 if type was head-on crash, 0 otherwise)	0.050	0.042	0.035	0.049	0.066	0.054
	(0.218)	(0.201)	(0.184)	(0.216)	(0.248)	(0.227)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Rider-injury severity (Frequency)						
Minor	741	210	641	647	294	713
Severe	277	92	378	305	129	256
Fatal	680	279	282	699	318	219
Total	1698	581	1301	1651	741	1188
Explanatory variables	Mean	Mean	Mean	Mean	Mean	Mean
	(Std)	(Std)	(Std)	(Std)	(Std)	(Std)
Rider characteristic/actions						
Male (1 if rider was male, 0 female)	0.786	0.820	0.782	0.791	0.829	0.767
	(0.409)	(0.383)	(0.412)	(0.406)	(0.375)	(0.422)
Pillion (1 if there was/were pillion(s), 0 otherwise)	0.342	0.376	0.262	0.337	0.365	0.287
	(0.474)	(0.485)	(0.439)	(0.472)	(0.481)	(0.452)
Speeding (1 if rider was speeding, 0 otherwise)	0.658	0.710	0.518	0.626	0.645	0.563
	(0.474)	(0.453)	(0.499)	(0.483)	(0.478)	(0.496)
Hit unexpected crossing object (1 if rider hit a unexpected crossing object, 0 otherwise)	0.229	0.196	0.277	0.260	0.256	0.232
	(0.420)	(0.397)	(0.447)	(0.439)	(0.436)	(0.422)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Overtake (1 if rider overtook improperly, 0 otherwise)	0.009	0.017	0.017	0.009	0.008	0.009
	(0.096)	(0.130)	(0.131)	(0.094)	(0.089)	(0.095)
Alcohol (1 if rider was under influence of alcohol, 0 otherwise)	0.028	0.012	0.114	0.015	0.024	0.111
	(0.165)	(0.109)	(0.318)	(0.124)	(0.154)	(0.315)
Fatigued (1 if rider was fatigued, 0 otherwise)	0.009	0.006	0.010	0.011	0.013	0.012
	(0.096)	(0.082)	(0.103)	(0.106)	(0.115)	(0.111)
Roadways attributes						
Main lane (1 if crash occurred on main lane, 0 otherwise)	0.079	0.099	0.045	0.033	0.024	0.019
	(0.270)	(0.300)	(0.208)	(0.179)	(0.154)	(0.137)
Frontage lane (1 if crash occurred on frontage lane, 0 otherwise)	0.055	0.063	0.018	0.055	0.045	0.015
	(0.228)	(0.244)	(0.134)	(0.228)	(0.209)	(0.125)
Work zone (1 if crash occurred on work zone, 0 otherwise)	0.022	0.015	0.014	0.018	0.021	0.016
	(0.149)	(0.123)	(0.120)	(0.135)	(0.145)	(0.128)
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise)	0.385	0.361	0.413	0.441	0.435	0.434
	(0.486)	(0.480)	(0.492)	(0.496)	(0.496)	(0.495)
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise)	0.323	0.323	0.419	0.305	0.309	0.403
	(0.467)	(0.468)	(0.493)	(0.460)	(0.462)	(0.490)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Undivided median (1 if crash occurred on undivided road, 0 otherwise)	0.339	0.339	0.447	0.320	0.330	0.410
	(0.473)	(0.473)	(0.497)	(0.466)	(0.470)	(0.492)
Flush median (1 if crash occurred on flush median road, 0 otherwise)	0.111	0.086	0.107	0.123	0.124	0.147
	(0.315)	(0.280)	(0.310)	(0.329)	(0.329)	(0.354)
Raised median (1 if crash occurred on raised median road, 0 otherwise)	0.290	0.292	0.225	0.262	0.248	0.223
	(0.454)	(0.455)	(0.418)	(0.439)	(0.432)	(0.416)
Depressed median (1 if crash occurred on depressed median road, 0 otherwise)	0.178	0.191	0.169	0.218	0.213	0.161
	(0.382)	(0.393)	(0.374)	(0.413)	(0.409)	(0.368)
Barrier median (1 if crash occurred on barrier median road, 0 otherwise)	0.080	0.091	0.047	0.075	0.083	0.057
	(0.271)	(0.288)	(0.213)	(0.264)	(0.277)	(0.232)
Concrete pavement (1 if crash occurred on concrete pavement road, 0 otherwise)	0.138	0.168	0.095	0.124	0.136	0.111
	(0.345)	(0.374)	(0.293)	(0.330)	(0.343)	(0.315)
Curve (1 if crash occurred on curve road, 0 otherwise)	0.117	0.132	0.102	0.093	0.120	0.118
	(0.321)	(0.339)	(0.304)	(0.291)	(0.325)	(0.323)
Grade (1 if crash occurred on graded road, 0 otherwise)	0.030	0.036	0.026	0.032	0.031	0.022
	(0.170)	(0.186)	(0.161)	(0.177)	(0.173)	(0.149)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Intersection (1 if crash occurred within 100m from intersection, 0 otherwise)	0.124	0.108	0.106	0.105	0.094	0.098
	(0.330)	(0.311)	(0.308)	(0.307)	(0.292)	(0.298)
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise)	0.075	0.061	0.073	0.056	0.059	0.048
	(0.265)	(0.241)	(0.260)	(0.231)	(0.236)	(0.215)
Bridge (1 if crash occurred on the bridge, 0 otherwise)	0.013	0.008	0.004	0.012	0.009	0.011
	(0.115)	(0.092)	(0.067)	(0.112)	(0.096)	(0.107)
Urban (1 if crash occurred in urban road, 0 rural)	0.222	0.206	0.156	0.202	0.187	0.168
	(0.416)	(0.405)	(0.363)	(0.401)	(0.390)	(0.374)
Environmental and temporal characteristics						
Wet road (1 if crash occurred on wet road, 0 otherwise)	0.058	0.061	0.036	0.049	0.041	0.037
	(0.234)	(0.241)	(0.186)	(0.217)	(0.200)	(0.190)
Rain (1 if crash occurred under rainy condition, 0 otherwise)	0.056	0.065	0.042	0.058	0.053	0.044
	(0.231)	(0.247)	(0.201)	(0.235)	(0.226)	(0.206)
Lit road (1 if crash occurred on lit road, 0 otherwise)	0.300	0.366	0.272	0.279	0.334	0.313
	(0.458)	(0.482)	(0.445)	(0.449)	(0.472)	(0.464)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Unlit road (1 if crash occurred on unlit road, 0 otherwise)	0.101	0.106	0.139	0.115	0.121	0.127
	(0.301)	(0.309)	(0.347)	(0.319)	(0.326)	(0.333)
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise)	0.121	0.154	0.122	0.139	0.156	0.161
	(0.327)	(0.362)	(0.327)	(0.346)	(0.363)	(0.368)
Peak hours (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise)	0.263	0.182	0.208	0.264	0.198	0.198
	(0.440)	(0.386)	(0.406)	(0.441)	(0.399)	(0.399)
Evening (1 if crash occurred between 18:00-23:59, 0 otherwise)	0.305	0.337	0.306	0.284	0.317	0.299
	(0.460)	(0.473)	(0.461)	(0.451)	(0.465)	(0.458)
Crash characteristics						
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise)	0.116	0.111	0.102	0.098	0.090	0.134
	(0.321)	(0.315)	(0.304)	(0.298)	(0.286)	(0.341)
Hit passenger car (1 if rider hit passenger car, 0 otherwise)	0.267	0.282	0.233	0.253	0.269	0.212
	(0.443)	(0.450)	(0.423)	(0.434)	(0.444)	(0.408)
Hit pickup truck (1 if rider hit pickup truck,0 otherwise)	0.271	0.270	0.262	0.334	0.284	0.265
	(0.444)	(0.444)	(0.439)	(0.471)	(0.451)	(0.442)

Table 4.2 Descriptive statistic of the explanatory variables and motorcyclist injury severity frequency (Cont.)

	2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise)	0.045	0.060	0.039	0.038	0.025	0.024
	(0.209)	(0.238)	(0.195)	(0.191)	(0.158)	(0.154)
Hit truck (1 if rider hit large truck, 0 otherwise)	0.137	0.123	0.033	0.149	0.105	0.023
	(0.344)	(0.329)	(0.178)	(0.356)	(0.307)	(0.151)
Rear-end (1 if type was rear-end crash, 0 otherwise)	0.357	0.351	0.325	0.393	0.375	0.326
	(0.479)	(0.477)	(0.468)	(0.488)	(0.484)	(0.469)
Side-swipe (1 if type was side-swipe crash, 0 otherwise)	0.283	0.278	0.217	0.271	0.249	0.204
	(0.451)	(0.448)	(0.412)	(0.444)	(0.433)	(0.403)
Single-crash (1 if type was single-crash crash, 0 otherwise)	0.181	0.185	0.292	0.164	0.206	0.308
	(0.385)	(0.389)	(0.454)	(0.371)	(0.405)	(0.462)
Head-on (1 if type was head-on crash, 0 otherwise)	0.101	0.113	0.063	0.089	0.086	0.079
	(0.302)	(0.317)	(0.244)	(0.284)	(0.281)	(0.270)

Table 4.3 Transferability test results between weekday, weekend and holiday crashes for each year (Chi-square, degree of freedom in parenthesis and confidence level in bracket)

Years	D_2	Weekday		Weekend		Holiday	
	D_1	Weekend	Holiday	Weekday	Holiday	Weekday	Weekend
2016		100.53 (32)	64.28 (32)	166.84 (25)	80.80 (25)	402.59 (21)	150.27 (21)
		[99.99%]	[99.99%]	[99.99%]	[99.99%]	[99.99%]	[99.99%]
2017		102.45 (28)	52.91 (28)	49.49 (21)	47.73 (21)	168.79 (18)	122.71 (18)
		[99.99%]	[99.70%]	[99.96%]	[99.93%]	[99.99%]	[99.99%]
2018		95.86 (22)	119.48 (22)	128.54 (22)	121.61 (22)	96.99 (31)	85.11 (31)
		[99.99%]	[99.99%]	[99.99%]	[99.99%]	[99.99%]	[99.99%]
2019		58.81 (26)	32.81 (26)	134.21 (23)	54.83 (23)	149.47 (19)	80.01 (19)
		[99.98%]	[83.24%]	[99/99%]	[99.98%]	[99/99%]	[99.99%]

Table 4.4 Temporal stability test results of weekday, weekend and holiday crashes (Chi-square, degree of freedom in parenthesis and confidence level in bracket)

t_2 / t_1	2016			2017			2018			2019		
	Weekday	Weekend	Holiday	Weekday	Weekend	Holiday	Weekday	Weekend	Holiday	Weekday	Weekend	Holiday
2016	-	-	-	170.65 (28) [99.99%]	81.38 (21) [99.99%]	71.77 (18) [99.99%]	192.81 (22) [99.99%]	64.55 (22) [99.99%]	**10.74 (31) [0.03%]**	137.72 (27) [99.99%]	95.82 (23) [99.99%]	51.82 (19) [99.99%]
2017	176.35 (36) [99.99%]	102.91 (25) [99.99%]	78.93 (21) [99.99%]	-	-	-	178.79 (22) [99.99%]	124.94 (22) [99.99%]	**11.76 (31) [0.07%]**	120.23 (27) [99.99%]	109.34 (23) [99.99%]	42.73 (19) [99.86%]
2018	136.95 (36) [99.99%]	98.08 (25) [99.99%]	146.76 (21) [99.99%]	78.62 (28) [99.99%]	91.05 (21) [99.99%]	110.38 (18) [99.99%]	-	-	-	98.58 (27) [99.99%]	110.35 (23) [99.99%]	103.05 (19) [99.99%]
2019	142.27 (36) [99.99%]	45.35 (25) [99.24%]	114.04 (21) [99.99%]	107.61 (28) [99.99%]	53.48 (21) [99.99%]	109.77 (18) [99.99%]	165.17 (22) [99.99%]	71.78 (22) [99.99%]	43.92 (31) [93.81%]	-	-	-

Se et al., 2021b; Yu et al., 2021), work zone crashes (Islam et al., 2020), effect of truck volume on non-truck-involved crashes (Fanyu et al., 2021), single- and multivehicle crashes (Hou et al., 2022), pedestrian–vehicle crashes (Alogaili and Mannering, 2022; Behnood and Mannering, 2016; Li et al., 2021c; Zamani et al., 2021), multivehicle crashes (Song et al., 2021), alcohol-impaired driving crashes (Yan et al., 2021a), crashes in adverse weather (Yan et al., 2021b), motorcycle crashes (Alnawmasi and Mannering, 2019; Chang et al., 2021), large-truck crashes (Behnood and Mannering, 2019), and animal–vehicle crashes (Al-Bdairi et al., 2020). From a temporal stability testing perspective, Hou et al., (2022) performed an extensive comparison of two types of tests (i.e., a global test across all time periods and a pairwise comparison of time periods) and the result showed that the pairwise comparison is more revealing than the global test and can provide more detailed insights into possible temporal variability. Hence, the current paper adopted the pairwise testing method for both transferability and temporal stability tests.

The tests were performed not only for differences between motorcyclist injuries resulting from weekday, weekend, and holiday motorcycle crashes but also for the temporal instability of each subgroup dataset. Initially, these tests determined whether motorcyclist injury severity models were statistically and significantly different between weekdays, weekends, and holidays for each yearly crash data from 2016 to 2019. These tests were conducted through a series of likelihood ratio tests as follow (Washington et al., 2020):

$$X^2 = -2[LL(\beta_{D_2D_1})_t - LL(\beta_{D_1})_t] \tag{4.5}$$

where t denotes the year of the crash (2016, 2017, 2018, or 2019), $LL(\beta_{D_2D_1})$ is the log-likelihood at convergence of the model estimated using converged parameters from D_2 (either weekday, weekend, or holiday model) on data D_1 (either weekday, weekend, or holiday data, and $D_2 \neq D_1$). $LL(\beta_{D_1})$ is the log-likelihood at convergence of the D_1 model using D_1 data with parameters no longer restricted to D_2 converged parameters. The tests were also reversed such that D_1 became D_2 and vice versa. To reject or accept the null hypothesis that the parameters are equal between D_1 and D_2 in a particular year, the resulting value of X^2 is χ^2 distributed with a degree of freedom equal to the number of estimated parameters. **Table 4.3** shows the results of the tests, indicating that the null hypothesis that the weekday, weekend, and holiday injury severity models are the same can be rejected with over 99% confidence level for each of the four years.

Lastly, another series of likelihood ratio tests were performed to determine whether the separately estimated weekday model, separately estimated weekend model, and separately estimated holiday model were temporally stable over the four-year period. For a particular time-of-year subgroup (either weekday, weekend, or holiday), the chi-square distributed test statistic can now be computed as follows:

$$X^2 = -2[LL(\beta_{t_2 t_1})_d - LL(\beta_{t_1})_d] \tag{4.6}$$

where *d* denotes the time-of-year of the crash (either weekday, weekend, or holiday), and $LL(\beta_{t_2 t_1})$ is the log-likelihood at convergence of the model estimated using converged parameters from t_2 (either 2016, 2017, 2018, or 2019 model) on data period t_1 (either 2016, 2017, 2018, or 2019, and $t_2 \neq t_1$). $LL(\beta_{t_1})$ is the log-likelihood at convergence of the t_1 model using t_1 data with parameters no longer restricted to t_2 converged parameters. The tests were also reversed such that time period t_1 became t_2 and vice versa. **Table 4.4** shows the results of these tests. Only 2 of 36 tests (holiday t_1 = 2016 vs. t_2 = 2018, and t_1 = 2017 vs. t_2 = 2018) were found to have relatively low confidence levels to reject the null hypothesis. However, the reverse of these two tests and all others supported the decision to reject the null hypothesis; that is, each of the time-of-year models (weekday, weekend, or holiday) are stable from one year to the next with a confidence level of over 99%. This will also be explained in detail in the discussion section below, focusing on individual explanatory variable findings.

4.7 Result and Discussion

This section discusses the significant variables and their impacts on motorcyclist injury severity probability in weekday, weekend, and holiday crashes from 2016 to 2019. **Table 4.5-4.8** present the estimation results of weekday, weekend, and holiday crashes for 2016 through 2019, respectively. While statistically significant random parameters were found in all models, heterogeneity in the means of random parameters were found in all other models except the 2017 and 2018 weekend models; however, heterogeneity in the variances of random parameters were found only in the 2017 weekday and 2018 holiday models. Additionally, **Tables 4.9-4.11**, respectively, show the summary of minor injury, severe injury, and fatal injury average marginal effects of the significant factors on resulting motorcyclist injury severity across time-of-year and yearly models.

The following sections are structured as follows: section 6.1 discusses the random parameter results and heterogeneity in means and variances using **Tables 4.5–4.8,** and sections 6.2–6.5 present the results and discussions of statistically significant parameters using the average marginal effect values in **Tables 4.9-4.11**.

4.7.1 Heterogeneity in means and variances

Starting with the 2016 weekday model (**Table 4.5**), U-turns, peak hours (between 7:00–8:59 and 16:00–17:59), hitting trucks, and single-motorcycle crashes produced statistically significant random parameters. Additionally, the average marginal effects show that motorcycle crashes within 100 m from U-turns and during peak hours increased the likelihood of severe injury (and decreased the likelihood of minor and fatal injuries (**Table 4.9-4.11**)). Meanwhile, hitting truck crashes significantly increased the likelihood of fatal injury whereas single-motorcycle crashes increased the likelihood of severe and fatal injuries. Regarding heterogeneity in means, the effects of peak-hour crashes and single-motorcycle crashes were found varying by the riding with pillion indicator, with the effect increasing the means of both random parameters. Conversely, the speeding indicator decreased the mean of single-motorcycle crashes, making minor injury less likely. Estimation result for the 2016 weekend model (**Table 4.5**) indicates that hitting-unexpected-crossing-object and midnight/early morning crashes (crashes occurring between 00:00 and 6:59) resulted in significant random parameters with their average marginal effects increasing the likelihood of severe and fatal injuries, respectively. Both variables also had statistically significant heterogeneity in mean. The asphalt-pavement indicator increased the mean of the hitting-unexpected-crossing-object indicator, making minor injury more likely, whereas the

Table 4.5 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2016 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Constant [MI]	1.548	1.27	1.355	1.68	2.929	6.00
Constant [SI]	-0.767	-3.87	0.414	0.53	1.529	3.49
Random parameters (normally distributed)						
Male (1 if rider was male, 0 female) [SI]	-	-	-	-	-0.631	-1.01
Standard deviation of "Male"	-	-	-	-	*2.846*	*2.05*
Pillion (1 if there was/were pillion(s), 0 otherwise) [MI]	-	-	-	-	-0.134	-0.29
Standard deviation of "Pillion"	-	-	-	-	*3.650*	*1.84*
Hit unexpected crossing object (1 if rider hit an unexpected crossing object, 0 otherwise) [MI]	-	-	-0.392	-0.94	-	-
Standard deviation of “Hit unexpected crossing object”	-	-	*2.017*	*1.69*	-	-
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise) [MI]	-4.992	-1.65	-	-	-	-
Standard deviation of “U-turn”	*3.123*	*1.68*	-	-	-	-
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise) [FI]	-	-	0.733	1.07	-	-
Standard deviation of “Midnight/early morning”	-	-	*3.239*	*1.76*	-	-
Peak hours (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise) [FI]	-0.947	-1.23	-	-	-	-

Table 4.5 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2016 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Standard deviation of "Peak hours"	*2.489*	*2.89*	-	-	-	-
Hit truck (1 if rider hit large truck, 0 otherwise) [FI]	4.207	2.56	-	-	-	-
Standard deviation of "Hit truck"	*2.439*	*2.32*	-	-	-	-
Single-crash (1 if type was single-crash crash, 0 otherwise) [MI]	1.774	1.49	-	-	-	-
Standard deviation of "single-crash"	*1.390*	*1.65*	-	-	-	-
Rider characteristics/actions						
Pillion (1 if there was/were pillion(s), 0 otherwise) [FI]	-	-	0.568	2.43	-	-
Alcohol (1 if rider was under influence of alcohol, 0 otherwise) [MI]	-1.759	-1.66	-	-	-	-
Fatigued (1 if rider was fatigued, 0 otherwise) [MI]	-	-	4.606	1.76	-	-
Roadways attributes						
Main lane (1 if crash occurred on main lane, 0 otherwise) [SI]	1.275	3.31	-	-	-	-
Frontage lane (1 if crash occurred on frontage lane, 0 otherwise) [SI]	0.913	2.47	-	-	-	-
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise) [FI]	-	-	0.812	2.15	-	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise) [MI]	-0.852	-2.83	-	-	-0.784	-2.26
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise) [FI]	-	-	1.708	2.93	-	-

Table 4.5 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2016 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Barrier median (1 if crash occurred on barrier median road, 0 otherwise) [MI]	-	-	1.553	3.68	-	-
Concrete pavement (1 if crash occurred on concrete pavement road, 0 otherwise) [SI]	-	-	-	-	1.284	3.01
Curve (1 if crash occurred on curve road, 0 otherwise) [MI]	-0.908	-2.79	-	-	-	-
Grade (1 if crash occurred on graded road, 0 otherwise) [FI]	0.880	1.71	-	-	-	-
Grade (1 if crash occurred on graded road, 0 otherwise) [SI]	-	-	1.551	2.40	-	-
Intersection (1 if crash occurred within 100m from intersection, 0 otherwise) [MI]	-0.432	-1.81	-	-	-	-
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise) [MI]	-	-	-1.331	-2.62	-	-
Bridge (1 if crash occurred on the bridge, 0 otherwise) [FI]	-	-	1.807	1.71	-	-
Urban (1 if crash occurred in urban road, 0 rural) [MI]	0.632	3.20	-	-	-	-
Urban (1 if crash occurred in urban road, 0 rural) [FI]	-	-	-0.598	-1.92	-	-
Environmental and temporal characteristics						
Wet road (1 if crash occurred on wet road, 0 otherwise) [FI]	-	-	3.842	2.27	-	-
Lit road (1 if crash occurred on lit road, 0 otherwise) [MI]	-	-	-	-	-1.154	-3.60

Table 4.5 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2016 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Unlit road (1 if crash occurred on unlit road, 0 otherwise) [SI]	-	-	-	-	1.505	2.85
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise) [FI]	1.001	3.23	-	-	-	-
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise) [SI]	-	-	-	-	-1.684	-2.54
Evening (1 if crash occurred between 18:00-23:59, 0 otherwise) [SI]	-	-	-	-	-0.890	-2.08
Crash characteristics						
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise) [FI]	-1.241	-3.92	-	-	-	-
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise) [MI]	-	-	0.739	2.29	-	-
Hit passenger car (1 if rider hit passenger car, 0 otherwise) [FI]	-0.685	-2.97	-	-	1.148	2.89
Hit pickup truck (1 if rider hit pickup truck,0 otherwise) [FI]	0.475	2.15	-	-	1.496	3.87
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise) [MI]	-	-	-1.381	-2.48	-	-
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise) [FI]	-	-	-	-	1.670	2.70
Hit truck (1 if rider hit large truck, 0 otherwise) [FI]	-	-	0.941	2.57	-	-
Side-swipe (1 if type was side-swipe crash, 0 otherwise) [FI]	-0.758	-2.79	-0.646	-1.96	-0.918	-2.11
Single-crash (1 if type was single-crash crash, 0 otherwise) [SI]	-	-	0.526	1.67	-0.757	-2.20
Head-on (1 if type was head-on crash, 0 otherwise) [SI]	0.527	1.73	-	-	-	-

Table 4.5 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2016 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Heterogeneity in means						
Male (1 if rider was male, 0 female) : Alcohol (1 if rider was under influence of alcohol, 0 otherwise) [SI]	-	-	-	-	1.192	1.70
Pillion (1 if there was/were pillion(s), 0 otherwise) : Hit unexpected crossing object (1 if rider hit a unexpected crossing object, 0 otherwise) [MI]	-	-	-	-	1.770	1.65
Hit unexpected crossing object (1 if rider hit a unexpected crossing object, 0 otherwise) : Concrete pavement (1 if crash occurred on Concrete pavement road, 0 otherwise) [MI]	-	-	3.651	1.99	-	-
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise) : Curve (1 if crash occurred on curve road, 0 otherwise) [FI]	-	-	4.490	1.76	-	-
Peak hour (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise) : Pillion (1 if there was/were pillion(s), 0 otherwise) [FI]	**0.972**	**1.69**	-	-	-	-
Single crash (1 if type was single-crash crash, 0 otherwise) : Pillion (1 if there was/were pillion(s), 0 otherwise) [MI]	**1.027**	**1.86**	-	-	-	-

Table 4.5 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2016 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Single crash (1 if type was single-crash crash, 0 otherwise) : Speeding (1 if rider was speeding, 0 otherwise) [MI]	**-3.381**	**-3.01**	-	-	**-**	**-**
Model Statistics						
Number of observations	1470		615		966	
Log-likelihood at convergence, LL(β)	-1200.706		-519.182		-916.242	
Log-likelihood at zero, LL(0)	-1614.960		-675.647		-1061.259	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.257		0.232		0.137	

Table 4.6 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2017 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Constant [MI]	0.656	2.24	2.224	2.37	1.633	5.16
Constant [SI]	-0.504	-1.64	2.035	2.54	0.891	5.94
Random parameters (normally distributed)						
Speeding (1 if rider was speeding, 0 otherwise) [MI]	-	-	-	-	2.066	1.51
Standard deviation of "Speeding"	-	-	-	-	*1.618*	*1.69*
Urban (1 if crash occurred in urban road, 0 rural) [FI]	-	-	-1.554	-1.15	-	-
Standard deviation of "Urban"	-	-	*3.726*	*1.66*	-	-
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise) [FI]	-	-	3.885	2.66	-	-
Standard deviation of "Midnight/early morning"	-	-	*4.666*	*2.17*	-	-
Hit truck (1 if rider hit large truck, 0 otherwise) [FI]	3.419	1.97	-	-	-	-
Standard deviation of "Hit truck"	*8.683*	*1.61*	-	-	-	-
Single-crash (1 if type was single-crash crash, 0 otherwise) [MI]	-0.500	-1.42	-	-	-	-
Standard deviation of "Single-crash"	*1.673*	*1.90*	-	-	-	-
Rider characteristic/actions						
Pillion (1 if there was/were pillion(s), 0 otherwise) [FI]	0.395	2.18	1.634	3.71	0.403	2.32
Speeding (1 if rider was speeding, 0 otherwise) [MI]	0.337	2.11	-	-	-	-

Table 4.6 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2017 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Hit unexpected crossing object (1 if rider hit a unexpected crossing object, 0 otherwise) [FI]	-	-	-1.518	-2.96	-	-
Fatigued (1 if rider was fatigued, 0 otherwise) [FI]	2.372	2.18	-	-	1.241	2.21
Roadways attributes						
Main lane (1 if crash occurred on main lane, 0 otherwise) [SI]	0.634	1.94	-	-	-	-
Frontage lane (1 if crash occurred on frontage lane, 0 otherwise) [FI]	-3.413	-3.62	-4.517	-1.87	1.485	2.22
Work zone (1 if crash occurred on work zone, 0 otherwise) [SI]	-	-	2.453	2.82	-	-
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise) [SI]	0.608	2.65	-	-	-	-
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise) [FI]	-	-	1.868	2.69	-	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise) [SI]	0.789	3.13	-	-	-	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise) [FI]	-	-	2.254	3.08	-	-
Raised median (1 if crash occurred on raised median road, 0 otherwise) [FI]	-0.477	-2.17	-	-	-	-
Depressed median (1 if crash occurred on depressed median road, 0 otherwise) [MI]	-0.316	-1.66	-	-	-	-
Barrier median (1 if crash occurred on barrier median road, 0 otherwise) [MI]	0.992	3.65	1.242	2.55	-	-
Concrete pavement (1 if crash occurred on concrete pavement road, 0 otherwise) [MI]	0.481	1.91	0.899	1.80	-	-

Table 4.6 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2017 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Curve (1 if crash occurred on curve road, 0 otherwise) [FI]	0.593	2.28	-	-	-	-
Curve (1 if crash occurred on curve road, 0 otherwise) [MI]	-	-	-	-	-0.480	-1.85
Grade (1 if crash occurred on graded road, 0 otherwise) [FI]	-	-	2.109	2.01	-	-
Intersection (1 if crash occurred within 100m from intersection, 0 otherwise) [SI]	**0.382**	**1.92**	0.735	1.85	-	-
Bridge (1 if crash occurred on the bridge, 0 otherwise) [FI]	**1.395**	**2.06**	-	-	-	-
Bridge (1 if crash occurred on the bridge, 0 otherwise) [MI]	-	-	-	-	**2.593**	**1.77**
Urban (1 if crash occurred in urban road, 0 rural) [MI]	**0.437**	**2.48**	-	-	**0.444**	**2.18**
Environmental and temporal characteristics						
Wet road (1 if crash occurred on wet road, 0 otherwise) [MI]	-1.009	-2.71	-	-	-	-
Lit road (1 if crash occurred on lit road, 0 otherwise) [FI]	0.932	3.85	-	-	-	-
Unlit road (1 if crash occurred on unlit road, 0 otherwise) [FI]	1.063	3.19	-	-	-	-
Unlit road (1 if crash occurred on unlit road, 0 otherwise) [MI]	-	-	-	-	-1.139	-2.25
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise) [FI]	1.148	3.62	-	-	-	-
Evening (1 if crash occurred between 18:00-23:59, 0 otherwise) [FI]	-	-	1.494	3.25	-	-

Table 4.6 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2017 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Crash characteristics						
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise) [FI]	-0.933	-2.96	-1.479	-2.43	-	-
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise) [MI]	-	-	-	-	0.543	2.30
Hit passenger car (1 if rider hit passenger car, 0 otherwise) [SI]	0.392	2.41	-	-	-	-
Hit pickup truck (1 if rider hit pickup truck,0 otherwise) [FI]	-	-	-	-	0.524	2.72
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise) [FI]	-	-	-	-	1.036	2.81
Hit truck (1 if rider hit large truck, 0 otherwise) [FI]	-	-	2.741	3.33	1.090	2.90
Rear-end (1 if type was rear-end crash, 0 otherwise) [FI]	-	-	1.008	2.40	-	-
Rear-end (1 if type was rear-end crash, 0 otherwise) [SI]	-	-	-	-	0.299	1.68
Head-on (1 if type was head-on crash, 0 otherwise) [FI]	-	-	1.699	2.56	1.110	3.72
Heterogeneity in means of random parameter						
Speeding (1 if rider was speeding, 0 otherwise) : Barrier median (1 if crash occurred on barrier median road, 0 otherwise) [MI]	-	-	-	-	-2.430	-1.65
Single-crash (1 if type was single-crash crash, 0 otherwise) : Hit unexpected crossing object (1 if rider hit a unexpected crossing object, 0 otherwise) [MI]	2.158	1.92	-	-	-	-

Table 4.6 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2017 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Heterogeneity in variance of random parameter						
Hit truck (1 if rider hit large truck, 0 otherwise) : Undivided median (1 if crash occurred on undivided road, 0 otherwise) [FI]	-1.153	-1.98	-	-	-	-
Model Statistics						
Number of observations	1485		483		1243	
Log-likelihood at convergence, LL(β)	-1325.497		-379.462		-1176.851	
Log-likelihood at zero, LL(0)	-1631.439		-530.630		-1365.575	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.188		0.285		0.138	

Table 4.7 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2018 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Constant [MI]	1.533	5.19	-0.577	-0.75	7.636	3.28
Constant [SI]	-0.039	-0.20	-0.839	-2.45	6.948	3.00
Random parameters (normally distributed)						
Male (1 if rider was male, 0 female) [FI]	-	-	-	-	-0.841	-1.08
Standard deviation of "Male"	-	-	-	-	*3.788*	*2.64*
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise) [FI]	-	-	1.344	2.01	-	-
Standard deviation of "Four lanes"	-	-	*4.625*	*2.01*	-	-
Barrier median (1 if crash occurred on barrier median road, 0 otherwise) [MI]	0.236	0.45	-	-	-	-
Standard deviation of "Barrier median"	*2.617*	*1.68*	-	-	-	-
Hit truck (1 if rider hit large truck, 0 otherwise) [FI]	2.328	3.87	-	-	-	-
Standard deviation of "Hit truck"	*2.177*	*1.93*	-	-	-	-
Rear-end (1 if type was rear-end crash, 0 otherwise) [FI]	-	-	-	-	-0.677	-0.87
Standard deviation of "Rear-end"	-	-	-	-	*2.318*	*1.68*
Side-swipe (1 if type was side-swipe crash, 0 otherwise) [FI]	-	-	-	-	-5.039	-1.68
Standard deviation of "Side-swipe"	-	-	-	-	*7.572*	*1.97*
Rider characteristic/actions						
Pillion (1 if there was/were pillion(s), 0 otherwise) [FI]	-	-	-	-	1.235	2.25

Table 4.7 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2018 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Speeding (1 if rider was speeding, 0 otherwise) [MI]	-	-	**1.031**	**2.15**	-	-
Speeding (1 if rider was speeding, 0 otherwise) [FI]	-	-	-	-	3.452	2.17
Hit unexpected crossing object (1 if rider hit a unexpected crossing object, 0 otherwise) [FI]	-	-	-	-	3.030	2.06
Overtake (1 if rider overtook improperly, 0 otherwise) [FI]	-	-	-	-	6.048	2.33
Alcohol (1 if rider was under influence of alcohol, 0 otherwise) [SI]	-	-	**1.775**	**2.08**	-	-
Roadways attributes						
Frontage lane (1 if crash occurred on frontage lane, 0 otherwise) [FI]	-1.676	-3.75	-1.712	-2.70	-	-
Work zone (1 if crash occurred on work zone, 0 otherwise) [FI]	-	-	-2.292	-1.88	-	-
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise) [MI]	-0.781	-4.48	-	-	-	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise) [MI]	-0.680	-3.11	-	-	-	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise) [FI]	-	-	1.967	1.75	-	-
Flush median (1 if crash occurred on flush median road, 0 otherwise) [MI]	-	-	-1.992	-3.62	-	-
Depressed median (1 if crash occurred on depressed median road, 0 otherwise) [MI]	-0.800	-3.78	-0.753	-2.04	-	-
Concrete pavement (1 if crash occurred on concrete pavement road, 0 otherwise) [MI]	0.386	1.95	-	-	-	-

Table 4.7 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2018 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Concrete pavement (1 if crash occurred on concrete pavement road, 0 otherwise) [SI]	-	-	-	-	-0.791	-3.02
Curve (1 if crash occurred on curve road, 0 otherwise) [SI]	-	-	0.816	2.12	-0.467	-1.90
Grade (1 if crash occurred on graded road, 0 otherwise) [MI]	**-0.855**	**-2.27**	-	-	-	-
Intersection (1 if crash occurred within 100m from intersection, 0 otherwise) [MI]	**-0.513**	**-2.86**	-	-	-0.390	-1.88
Intersection (1 if crash occurred within 100m from intersection, 0 otherwise) [SI]	-	-	1.189	3.04	-	-
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise) [FI]	-	-	-1.511	-1.92	-	-
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise) [SI]	-	-	-	-	-0.621	-1.96
Bridge (1 if crash occurred on the bridge, 0 otherwise) [SI]	-	-	3.644	2.60	-	-
Urban (1 if crash occurred in urban road, 0 rural) [FI]	**-0.545**	**-3.21**	-	-	-1.461	-2.10
Environmental and temporal characteristics						
Wet road (1 if crash occurred on wet road, 0 otherwise) [MI]	-1.909	-2.55	-	-	-	-
Wet road (1 if crash occurred on wet road, 0 otherwise) [FI]	-	-	3.017	2.99	-	-
Rain (1 if crash occurred under rainy condition, 0 otherwise) [MI]	-	-	1.497	1.90	-	-
Rain (1 if crash occurred under rainy condition, 0 otherwise) [SI]	-	-	-	-	0.546	1.66

Table 4.7 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2018 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Lit road (1 if crash occurred on lit road, 0 otherwise) [MI]	-	-	-	-	-0.427	-2.72
Unlit road (1 if crash occurred on unlit road, 0 otherwise) [FI]	0.912	2.20	-	-	-	-
Unlit road (1 if crash occurred on unlit road, 0 otherwise) [MI]	-	-	-2.435	-2.38	-0.557	-2.72
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise) [FI]	1.225	3.57	-	-	3.178	2.98
Peak hours (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise) [FI]	-	-	-	-	1.328	2.18
Evening (1 if crash occurred between 18:00-23:59, 0 otherwise) [FI]	-	-	-	-	1.209	2.00
Crash characteristics						
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise) [FI]	-0.377	-1.91	-1.344	-3.11	-	-
Hit passenger car (1 if rider hit passenger car, 0 otherwise) [MI]	-	-	0.846	2.69	-	-
Hit passenger car (1 if rider hit passenger car, 0 otherwise) [FI]	-	-	-	-	2.186	2.54
Hit pickup truck (1 if rider hit pickup truck,0 otherwise) [MI]	-0.283	-2.08	-	-	-	-
Hit pickup truck (1 if rider hit pickup truck,0 otherwise) [FI]	-	-	-	-	2.050	2.54
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise) [MI]	-0.529	-1.85	-	-	-	-
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise) [FI]	-	-	-	-	4.471	2.86
Hit truck (1 if rider hit large truck, 0 otherwise) [FI]	-	-	0.895	2.19	6.008	2.81

Table 4.7 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2018 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Side-swipe (1 if type was side-swipe crash, 0 otherwise) [SI]	-0.693	-3.82	-	-	-	-
Side-swipe (1 if type was side-swipe crash, 0 otherwise) [MI]	-	-	1.132	2.21	-	-
Single-crash (1 if type was single-crash crash, 0 otherwise) [SI]	-0.336	-1.66	-	-	-	-
Head-on (1 if type was head-on crash, 0 otherwise) [FI]	1.050	5.36	-	-	-	-
Head-on (1 if type was head-on crash, 0 otherwise) [MI]	-	-	-	-	-0.488	-1.77
Heterogeneity in means of random parameter						
Hit truck (1 if rider hit large truck, 0 otherwise) : Hit unexpected crossing object (1 if rider hit a unexpected crossing object, 0 otherwise) [MI]	-1.978	-2.34	-	-	-	-
Rear-end (1 if type was rear-end crash, 0 otherwise) : Four lanes (1 if crash occurred on four-lanes road, 0 otherwise) [FI]	-	-	-	-	**-1.756**	**-1.81**
Heterogeneity in variance of random parameter						
Side-swipe (1 if type was side-swipe crash, 0 otherwise) : Flush median (1 if crash occurred on flush median road, 0 otherwise) [FI]	-	-	-	-	0.849	2.19
Model Statistics						
Log-likelihood at convergence, LL(β)	-1514.486		-470.562		-1246.995	
Log-likelihood at zero, LL(0)	-1865.444		-638.294		-1429.295	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.188		0.263		0.128	

Table 4.8 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2019 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Constant [MI]	1.158	2.94	-0.092	-0.18	2.482	7.81
Constant [SI]	0.750	2.25	-0.556	-1.73	1.496	5.55
Random parameters (normally distributed)						
Male (1 if rider was male, 0 female) [MI]	-	-	-	-	-0.514	-2.25
Standard deviation of "Male"	-	-	-	-	*1.334*	*1.67*
Pillion (1 if there was/were pillion(s), 0 otherwise) [FI]	0.589	3.02	-	-	-	-
Standard deviation of "Pillion"	*1.375*	*2.43*	-	-	-	-
Hit unexpected crossing object (1 if rider hit an unexpected crossing object, 0 otherwise) [FI]	-0.151	-0.40	-	-	-	-
Standard deviation of "hit unexpected crossing object"	*2.047*	*2.82*	-	-	-	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise) [FI]	-	-	1.896	1.58	-	-
Standard deviation of "Two lanes"	-	-	*3.216*	*2.39*	-	-
Raised median (1 if crash occurred on raised median road, 0 otherwise) [FI]	-	-	-0.859	-1.60	-	-
Standard deviation of "Raised median"	-	-	*2.011*	*2.22*	-	-
Rider characteristic/actions						
Pillion (1 if there was/were pillion(s), 0 otherwise) [FI]	-	-	0.567	2.22	0.434	2.30
Speeding (1 if rider was speeding, 0 otherwise) [FI]	0.470	1.90	-	-	-	-

Table 4.8 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2019 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Hit unexpected crossing object (1 if rider hit an unexpected crossing object, 0 otherwise) [FI]	-	-	**-0.567**	**-1.90**	-	-
Overtake (1 if rider overtook improperly, 0 otherwise) [FI]	1.523	2.19	-	-	-	-
Alcohol (1 if rider was under influence of alcohol, 0 otherwise) [FI]	-	-	**-3.168**	**-2.34**	**-0.918**	**-2.64**
Fatigued (1 if rider was fatigued, 0 otherwise) [SI]	-	-	-	-	**1.035**	**1.66**
Roadways attributes						
Main lane (1 if crash occurred on main lane, 0 otherwise) [SI]	-	-	-	-	1.468	2.61
Frontage lane (1 if crash occurred on frontage lane, 0 otherwise) [MI]	-	-	-	-	-1.161	-1.67
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise) [FI]	0.922	4.59	0.506	1.72	-	-
Undivided median (1 if crash occurred on undivided road, 0 otherwise) [FI]	0.836	3.37	-	-	-	-
Barrier median (1 if crash occurred on barrier median road, 0 otherwise) [MI]	0.678	2.36	-	-	-	-
Concrete pavement (1 if crash occurred on concrete pavement road, 0 otherwise) [MI]	0.435	2.41	-	-	-	-
Curve (1 if crash occurred on curve road, 0 otherwise) [SI]	0.543	2.41	-	-	-	-
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise) [SI]	0.650	2.45	-	-	-	-
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise) [FI]	-	-	1.379	2.78	-	-
Urban (1 if crash occurred in urban road, 0 rural) [SI]	-0.444	-2.35	-	-	-	-

Table 4.8 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2019 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Urban (1 if crash occurred in urban road, 0 rural) [FI]	-	-	-0.782	-2.38	-	-
Environmental and temporal characteristics						
Rain (1 if crash occurred under rainy condition, 0 otherwise) [MI]	-	-	1.437	1.99	-	-
Lit road (1 if crash occurred on lit road, 0 otherwise) [FI]	0.912	4.75	-	-	-	-
Unlit road (1 if crash occurred on unlit road, 0 otherwise) [FI]	1.183	4.93	1.479	3.07	-	-
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise) [FI]	0.988	4.58	-	-	1.968	6.56
Peak hours (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise) [FI]	-	-	-	-	0.476	1.82
Evening (1 if crash occurred between 18:00-23:59, 0 otherwise) [FI]	-	-	-	-	0.670	2.69
Crash characteristics						
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise) [FI]	-1.139	-3.62	-1.397	-2.88	-	-
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise) [SI]	-	-	-	-	-0.764	-2.78
Hit passenger car (1 if rider hit passenger car, 0 otherwise) [MI]	0.312	2.11	-	-	-	-
Hit passenger car (1 if rider hit passenger car, 0 otherwise) [FI]	-	-	-0.665	-2.25	-	-
Hit pickup truck (1 if rider hit pickup truck,0 otherwise) [FI]	-	-	-	-	0.565	2.74
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise) [MI]	-0.771	-2.23	-	-	-	-

Table 4.8 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2019 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Hit truck (1 if rider hit large truck, 0 otherwise) [FI]	1.397	6.32	2.352	4.39	1.507	3.23
Rear-end (1 if type was rear-end crash, 0 otherwise) [FI]	-0.579	-2.96	-	-	-	-
Side-swipe (1 if type was side-swipe crash, 0 otherwise) [FI]	-0.946	-4.25	-	-	-	-
Single-crash (1 if type was single-crash crash, 0 otherwise) [MI]	-	-	-	-	0.823	3.02
Head-on (1 if type was head-on crash, 0 otherwise) [MI]	**-0.595**	**-2.28**	-	-	-	-
Head-on (1 if type was head-on crash, 0 otherwise) [FI]	-	-	**1.659**	**3.15**	0.516	1.73
Heterogeneity in means of random parameters						
Male (1 if rider was male, 0 female): Rear-end (1 if type was rear-end crash, 0 otherwise) [MI]	-	-	-	-	0.442	1.65
Male (1 if rider was male, 0 female): Side-swipe (1 if type was side-swipe crash, 0 otherwise) [MI]	-	-	-	-	0.638	2.01
Pillion (1 if there was/were pillion(s), 0 otherwise) : Peak hours (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise) [FI]	0.567	1.82	-	-	-	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise) : Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise) [FI]	-	-	2.588	1.72	-	-

Table 4.8 Random parameters model with heterogeneity in the means and variances results for motorcyclist-injury severity for 2019 (parameters defined for: [MI] Minor Injury; [SI] Severe Injury; [FI] Fatal Injury) (Cont.)

Variables	Weekdays		Weekends		Holidays	
	Estimated parameters	Z value	Estimated parameters	Z value	Estimated parameters	Z value
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise) : Evening (1 if crash occurred between 18:00-23:59, 0 otherwise) [FI]	-	-	-1.336	-1.79	-	-
Model Statistics						
Number of observations	1651		741		1188	
Log-likelihood at convergence, LL(β)	-1521.033		-675.999		-1041.188	
Log-likelihood at zero, LL(0)	-1813.809		-814.072		-1305.151	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.161		0.170		0.202	

curve-road indicator increased the mean of the midnight/early morning indicator, rendering fatal injury more likely. The result for the 2016 holiday model (**Table 4.5**) shows that the male rider and pillion indicators produced significant random parameters with their average marginal effects increasing the probability of severe and fatal injuries, respectively. Regarding heterogeneity in mean, the alcohol indicator increased the mean of the male-rider indicator, making severe injury more likely, whereas hitting-unexpected-crossing-object increased the mean of the riding with pillion indicator, making minor injury more likely.

Regarding the 2017 weekday model (**Table 4.6**), two indicators resulted in significant random parameters: hitting large trucks and single-motorcycle crashes. Based on the average marginal effect (**Table 4.10-4.11)**, motorcyclists that hit trucks had a higher probability of sustaining fatal injury, whereas single-motorcycle crashes increased the likelihood of severe injury. For heterogeneity in means, the effect of single-motorcycle crashes was found varying by hitting-unexpected-crossing-object (increasing the mean of random parameters, rendering minor injury more likely). Additionally, the hitting-truck random parameter produced significant heterogeneity in variance, with the effect of undivided road indicator decreasing the variance of random parameters and reflecting lower variability among motorcycle crashes involving trucks on undivided median roads. The estimation result for the 2017 weekend model (**Table 4.6**) shows that urban and midnight/early morning indicators produced statistically significant random parameters, with their average marginal effects increasing the likelihood of motorcyclist severe and fatal injuries, respectively. The estimation result for the 2017 holiday model (**Table 4.6**) indicates that the speeding indicator resulted in random parameter with the average marginal effect increasing the likelihood of minor injury. In terms of heterogeneity in mean, crashes on barrier median roads decreased the mean of the speeding-rider indicator, rendering severe and fatal injuries more likely.

According to the 2018 weekday model result (**Table 4.7**), the barrier median and hitting truck indicators produced statistically significant random parameters with the average marginal effects increasing the likelihood of motorcyclist severe and fatal injuries, respectively. The hitting-truck indicator produced a significant heterogeneity in means, with its effect varying by hitting-unexpected-crossing-object (decreasing the mean of random parameters). In this case, a motorcyclist hitting a truck as an unexpected crossing object increased the probability of minor and severe injuries. For the 2018 weekend model (**Table 4.7**), crashes on four-lane highways produced a significant random parameter with the average marginal effect increasing the likelihood of fatal injury. Estimation result for the 2018 holiday model (**Table 4.7**) shows that male riders, rear-end crashes, and side-swipe crashes produced statistically significant random parameters. Based on the average marginal effect, male riders and side-swipe crashes led to higher probabilities of motorcyclists sustaining fatal injury whereas rear-end crashes decreased the likelihood of fatal injury (while increasing the likelihood of minor and severe injuries). In addition, the rear-end crash indicator also produced a significant heterogeneity in means, with its effect varying and its mean decreasing by the four-lane road indicator, rendering minor and severe injuries more likely. For heterogeneity in variance, side-swipe crashes were found to decrease variability among crashes on flush median roads.

As indicated in **Table 4.8** for the 2019 weekday model, riding with pillion and hitting-unexpected-crossing-object indicator resulted in statistically significant random parameters with both their average marginal effects increasing the likelihood of fatal injury. The riding with pillion indicator also produced significant heterogeneity in means, with its effect varying by peak-hour crashes (increasing the means of the random parameters and rendering fatal injury more likely). The estimation result for the 2019 weekend model (**Table 4.8**) indicates that the two-lane road and raised-median indicator produced significant random parameters with their average marginal effects increasing and decreasing the likelihood of fatal injury, respectively. For heterogeneity in means, the midnight/early morning indicator increased the mean of the two-lane indicator (making fatal injury more likely) whereas the evening indicator decreased it (making fatal injury less likely). Lastly, the model result of the 2019 holiday crashes (**Table 4.8**) shows that male riders produced significant random parameter with average marginal effect decreasing the likelihood of minor injury while increasing that of severe and fatal injuries. This random parameter also produced significant heterogeneity in means, with its effect varying by rear-end crashes and side-swipe crashes (both of which increased the mean of the random parameter, rendering minor injury more likely).

4.7.2 Rider-related characteristics

As shown in **Tables 4.9–4.11**, the male-rider indicator was statistically significant in only holiday models (2016, 2018, and 2019, but not 2017), with the average marginal effect increasing the likelihood of severe injury in 2016 and fatal injury in 2018 and 2019 holiday crashes (the magnitude of fatal injury marginal effect is higher in the 2018 model than in 2019 model). Additionally, male-rider indicator was not significant in all periods of weekday and weekend models, indicating nontransferability among time-of-year models of motorcycle crashes (i.e., holiday motorcycle crashes should be modeled separately). Although time-of-year was not reported, some previous studies supported this finding (Shaheed and Gkritza, 2014; Xin et al., 2017b), whereas other study contradicted the current findings (Jung et al., 2013). This variability in the findings could possibly be due to different attitude and behavior between gender of the motorcyclists across studies (Uttra et al., 2020). Possible explanation for this finding is that male riders may be more likely to shift their personality type toward being extrovert (who are more likely to take higher risk to experience the excitement and thrill) during the Songkran and New Year holidays. Additionally, the extrovert motorcyclists are more likely to have higher vulnerability, compared to the introvert type (Haque et al., 2010). In addition, compared to females, males are more prone to aggressive driving, overuse of drug and alcohol, and risky behaviours (Ulfarsson and Mannering, 2004; Yan et al., 2021c).

Compared with the lone rider, the indicator for riders with pillion was statistically significant in all year models and most of the time-of-year models (except 2016 weekday and 2018 weekday and weekend) with the stable average marginal effects across all models increasing the likelihood of fatal injury (**Table 4.11)**. However, the magnitude of marginal effects fluctuated across time-of-year and yearly models. This finding is intuitive and consistent with the previous works (Alnawmasi and Mannering, 2019; Li et al., 2021a). Possible explanations for this are that having two or more people involved in the crash could increase the chances of the crashes being classified with a higher severity ranking (Quddus et al., 2002), and the pillion may have peer influences on riders' risk taking behavior such as speeding and aggressive driving (Moller and Haustein, 2014; Aldridge et al., 1999). Additionally, riding with pillion could also alter the braking distances due additional weight when a passenger is present (Alnawmasi and Mannering, 2019). Although the reason for the unstable effects of the weekday models is not entirely clear, the stable effect increasing the chances of fatal injury of this variable during weekends and both holidays (Songkran and Western New Year) should be mainly focused to improve motorcyclist safety in the context of developing countries in Southeast Asia.

The indicator for riders involved in speeding-related crashes showed a remarkably unstable effect across different time-of-year and yearly models. On weekdays, for example, the speeding rider variable produced significant parameters in only the 2017 and 2019 model, with the average marginal effects increasing the likelihood of minor injury in 2017 and fatal injury in 2019 (**Table 4.9-4.11)**. For weekend crash models, speeding riders had a higher probability of sustaining minor injury in the 2018 and 2019 models. However, for the holiday crash models, the marginal effect of this indicator increased the likelihood of minor injury in the 2017 model and fatal injury in the 2018 model. Some of these results may seem counterintuitive, as speeding physically increases crash impact as well as injury severity. However, there are two possible reasons for these findings: (1) The majority of the motorcycle crashes in the current study identified speeding as the cause of crash and also contained a relatively high proportion of minor injuries; therefore, indicator for speeding-related crashes was likely to result in unobserved heterogeneity (i.e., its effect significantly varies across cohort of observations; for instance, it affected the mean of random parameters (**Table 4.5**), produced significant random parameter (**Table 4.6**)) or produced fixed-effects toward the majority of the observed injury severities. (2) Considering the effect of speeding-related crashes increasing the possibility of minor injury in the earlier period (2017) and increasing the risk of fatal injury in the latest period (2019), this may be partially due to changes (or may be an improvement of accuracy/correctness) in police-reporting practices over time to more frequently identifying speeding as the cause of severe crashes. Although temporal instabilities across yearly model were observed, main focus should be on the effect of this variable in the most recent periods to further help improve motorcyclist safety, particularly Songkran and New Year holiday (in the 2018 model with relatively high fatal injury marginal effect of 0.1085) and weekdays (in the 2019 model with fatal injury marginal effect of 0.0531).

The hitting-unexpected-crossing-object indicator was statistically significant in various yearly and time-of-year models with unstable effects. For weekend crashes, this indicator was found to increase the probability of severe injury in the 2016, 2017, and 2019 models (**Table 4.10)**. Conversely, it was found to increase the likelihood of fatal injury in the 2018 holiday crashes and the 2019 weekday crashes (**Table 4.11)**. The possible explanation for the observed temporal instability of this variable is unclear (or may be due to possible unmeasured factors); however, main focus should also be on the lastest period, particularly both holiday periods with the highest positive fatal injury marginal effect relative to weekdays and weekends (**Table 4.11)**.

The variable reflecting improper overtaking was statistically significant in only the 2018 holiday and 2019 weekday models with both average marginal effects increasing the likelihood of fatal injury (**Table 4.11)**. One possible explanation is that crashes involving motorcyclists overtaking improperly/illegally are prone to be severe crash types such as head-on crash and high speed crash. Previous studies also reported that improper overtaking is among the most serious causes of fatalities in motorcycle crashes (Kashani et al., 2012; Se et al., 2021). In addition to the observed temporal instability across all time-of-year models, the marginal effect of fatal injury in the 2018 holiday model is over three times higher than in the 2019 weekday model **(Table 4.11)**, indicating that crashes during the two holiday periods are far more dangerous for motorcyclists overtaking other vehicle types improperly or illegally.

The indicator for riders under the influence of alcohol was significant in only the 2016 weekday model (and insignificant in all other periods), with the marginal effect increasing the likelihood of severe and fatal injuries. However, this indicator produced significant parameters in two weekend models (2018 and 2019) and one holiday model (2019), with the stable marginal effects increasing the likelihood of severe injury (**Table 4.10**). This finding is intuitive, and previous studies also reported similar finding that alcohol consumption was more likely to increase the injury severity level of motorcycle crashes (Schneider & Savolainen, 2011; Rifaat et al., 2012; Shaheed & Gkritza, 2014 ;Islam, 2021). With the worsening effect of this indicator in 2019, more attentions should be paid to improving the safety of motorcyclists associated with alcohol consumption, particularly during the two holidays when people are likely to travel for entertainment purposes (in which the alcohol-related motorcycle crashes are overrepresented (**Table 4.2**)).

Lastly, the variable reflecting fatigued riders was found significant in only one weekend model (2016) with the marginal effect increasing the likelihood of minor injury (**Table 4.9)**. However, fatigued riders were found to increase the likelihood of fatal injury in 2017 weekdays and holidays period, and increase the likelihood of severe injury in the 2019 holiday model (**Table 4.10-4.11)**. This may be attributed to the possibility that fatigue can reduce the reaction time, alertness, and ability to control the motorcycle, thereby encouraging strong impact crash due to unawareness of the potential collision (Se et al., 2020b). The reason for the shift in effect during the later period is possibly due to the changes in reporting practices of the police officers to frequently identifying the cause of severe crashes as fatigue in riders (Behnood and Mannering, 2015; Se et al., 2021b). In addition to the significant effect in the 2017 and 2019 holiday models, the frequency of fatigue-related motorcycle crashes during the two holidays, as indicated in **Table 4.2**, were higher than fatigue-related crashes on weekdays and weekends, indicating the need to also focus on this issue during the two holiday seasons.

4.7.3 Roadway-related characteristics

Compared to roads without frontage lanes, the variable reflecting crashes on main lanes was statistically significant only in the 2016 weekday, 2017 weekday, and 2019 holiday models with their average marginal effects increasing the likelihood of severe injury (highest in the 2016 weekday model in terms of magnitude (**Table 4.10**)). Meanwhile, for the weekday models, indicator for crashes on frontage lane was statistically significant in the 2016, 2017, and 2018 models with the average marginal effects increasing the likelihood of severe injury in 2016 (decreasing other injury severities) and increasing the likelihood of minor and severe injuries in the 2017 and 2018 models (**Table 4.9-4.10**). For the weekend models, this variable was found significant in the 2017 and 2018 models with their average marginal effects decreasing the likelihood of fatal injury (and increasing the probability of minor and severe injuries). Conversely, this variable resulted in a significant factor in the 2017 and 2019 holiday models with their average marginal effects increasing the likelihood of fatal injury (**Table 4.11)**. These findings justify not only temporal instability but also nontransferability of the effects of main lane and frontage lane on riders injury severities. Although frontage lanes provide motorcycle users with a better safety than roads without them, the nature of the two holiday periods still pose a significant risk of sustaining severe injury to motorcyclists who use frontage lane roads. However, motorcycle crashes on frontage lane are less likely to increase injury severity due to low traffic volumes and low posted speed limits of frontage lane roads which commonly serve traffic of the community areas or urban areas (Se et al., 2021a; Champahom et al., 2020a; Xin et al., 2017b). Possible reasons that differentiate the effect of frontage lane indicator in the holiday models from weekday and weekend models may be due to the increase in traffic volumes on frontage lane roads caused by local people and their cultural activities such as splashing water on the motorcyclist and passenger of the various types of vehicle during the Songkran holiday period (also well-known as water festival) which also potentially pose safety risk.

The variable reflecting motorcycle crashes within work zones was statistically significant in only the 2017 and 2018 weekend models with the average marginal effects increasing the likelihood of severe injury in the 2017 model and the probability of minor and severe injury in the 2018 model (**Table 4.9-4.10**). Similarly, previous studies also reported that work zone motorcycle-crashes during weekends were more likely to increase the likelihood of severe injury, particularly late at night (Al-Bdairi, 2020; Islam, 2022). Possible reason that this variable was not found significant in the holiday models may be attributed to the possibility that work zone areas are normally and temporarily closed during the holiday periods; therefore, the construction companies are expected to firmly organize and improve the traffic safety conditions prior to the holidays.

For weekend crashes, compared to roads with six or more lanes, the variable reflecting motorcycle crashes on four-lane roads was statistically significant in all periods from 2016 to 2019 models, with stable average marginal effects increasing the likelihood of fatal injury (but fluctuating over time, **Table 4.11**). Similarly, this variable was significant in the 2017 to 2019 weekday models, with the average marginal effects increasing the likelihood of severe injury in the 2017 model (**Table 4.10**) and fatal injury in the 2018 and 2019 models (**Table 4.11**). However, this indicator was not significant in all holiday models. Meanwhile, compared to roads with higher number of lanes, the variable reflecting motorcycle crashes on two-lane roads was statistically significant in the 2016 to 2018 weekday models, with their average marginal effects increasing the likelihood of severe and fatal injuries (**Table 4.10-4.11**). Likewise, this indicator was significant in all weekend models from 2016 to 2018, with the stable average marginal effects increasing the likelihood of fatal injury (**Table 4.11**). However, for holiday crashes, this indicator was significant in only the 2016 model with its marginal effect increasing the likelihood of fatal injury (**Table 4.11**). Possible reasons for these two variables that were not found statistically significant in all holiday models may be attributed to the possibility that the traffic characteristics of two-lanes, four-lanes or more lane roads during the two holidays (e.g., traffic density and operating speed based on high traffic volumes) are similar to one another. However, traffic attributes and operating speed characteristics are considerably different between two-lane, four-lane and more lane roads during the normal weekdays and weekends, thus potentially making these indicators significant in only the weekday and weekend models. Based on the marginal effect magnitudes (**Table 4.11**), for the weekday and weekend models, the fatal injury probabilities of two-lane road crashes are remarkably higher than crashes occurring on four-lane roads. This may be due to the fact that motorcycle crashes on two-lanes roads (commonly undivided road) are prone to be head-on crashes which are highly associated with higher injury-severity level (Schneider and Savolainen, 2011), and possibly due to higher likelihood (or percentage share) of striking against heavy vehicles than road with higher number of lanes (Naqvi and Tiwari, 2018).

Regarding median types, the variable reflecting crashes on undivided roads and flush median roads were significant in the 2019 weekday and 2018 weekend models, respectively, with the marginal effects increasing the likelihood of fatal injury

(**Table 4.11**). These findings are intuitive since undivided roads (in Thailand) are normally two-lane roads, and motorcycle crashes on two-lanes road or flush median road are likely to be severe head-on crashes. Conversely, the variable reflecting crashes on raised median roads was statistically significant in only the 2017 weekday and 2019 weekend models with the average marginal effects decreasing the probability of fatal injury (and increasing the likelihood of minor and severe injuries (**Table 4.9-4.11**)). For weekday crashes, the indicator for crashes on barrier median roads was significant in only the 2017, 2018, and 2019 models, with unstable marginal effects increasing the probability of minor injury in the 2017 and 2019 models and increasing the probability of severe injury in the 2018 model (**Table 4.9-4.10)**. Also, motorcycle crashes on barrier median roads led to a higher probability of minor injury in the 2016 and 2017 weekend models. Possible reason for crashes on raised and barrier median roads decreasing likelihood of fatal injury may be attributed to the fact that both median types could limit the turning option and redirect this action to a safer location, thereby reducing the risk of head-on collision and other unsafe/illegal overtaking (Se et al., 2021a). The indicator for crashes on depressed median roads was significant in the 2017 weekday and 2018 weekday and weekend models with their marginal effects increasing the likelihood of severe and fatal injuries. This finding is consistent with the finding of Champahom et al. (2022). One possible reason for this is that depressed median roads (in Thailand) are commonly built between cities and provinces (commonly across rural areas) and serve mixed- and high-speed traffic; therefore, motorcycle crashes on this road type are prone to severe crashes. Although the possible source of the observed temporal instability is unclear, the reason that these indicators were not found statistically significant in all holidays models could be the same as above explanations for the effect of number of lanes.

Compared to crashes on asphalt pavement, the variable reflecting motorcycle crashes on concrete pavements was statistically significant in the 2017 to 2019 weekday and 2017 weekend models, with the stable average marginal effects increasing the likelihood of minor injury and decreasing that of severe and fatal injuries (**Table 4.9-4.11**). A possible reason may be that motorcyclists are more likely to use lower speed when riding on concrete road compared to asphalt pavement road (probably because concrete road provides a noisy and less stable riding experience (Se et al., 2021a)). Conversely, this variable shows different effects for holiday crashes. For example, in the 2016 and 2018 holiday models, the average marginal effects of this indicator increased the likelihood of severe and fatal injuries, respectively. This may be attributed to the possibility that crashes on concrete roads could be more severe due to body impacting with higher roughness, friction and solidness of the concrete surface compared to asphalt pavement's surface (given that the traffic characteristics and operating speed are likely to be the same for both types of road during the two holiday seasons). Again, this finding indicates not only significant temporal instability but also nontransferability among time-of-year and yearly models.

The variable reflecting crashes on curve roads was statistically significant in multiple models. For weekday crashes, this indicator was significant in the 2016, 2017, and 2019 models, with the stable average marginal effects increasing the likelihood of severe and fatal injuries (**Table 4.10-4.11**). Additionally, this indicator was also significant in the 2017 holiday model (decreasing the probability of minor injury), 2018 holiday model (increasing the likelihood of fatal injury), and 2018 weekend model (increasing the likelihood of severe injury). Despite temporal instability (i.e., insignificant in some models), all time-of-year models generated the consistent results showing that motorcycle crashes on curve roads increased the likelihood of severe or fatal injury. Since this indicator was significant in some of the latest periods (2018 and 2019), more efforts should be given to improve motorcycle safety on the curve road segment. Previous work also reported similar findings (Chang et al., 2016; Xin et al., 2017b). On the other hand, the variable signifying crashes on graded roads was statistically significant in the 2016 and 2018 weekday models and 2016 and 2017 weekend models, with marginal effects increasing the likelihood of severe injury in the 2016 weekend model and fatal injury in all other three models (but at different magnitudes and the highest being the marginal effect of fatal injury in the 2017 weekend model). One possible explanation may be due to the increased difficulties in motorcycle speed controlling at such locations (Chang et al., 2021). This finding is also intuitive and in line with previous studies (Chang et al., 2016, 2021; Alnawmasi and Mannering, 2019).

The variable reflecting crashes within 100 m from intersections was statistically significant in the 2016, 2017, and 2018 weekday models, with average marginal effects increasing severe and fatal injuries probability in the 2016 and 2018 model and increasing the likelihood of severe injury in the 2017 model (**Table 4.10-4.11**). For weekend crashes, this variable was significant in only the 2017 and 2018 models, with both average marginal effects increasing the likelihood of severe injury (**Table 4.10**). Likewise, it was also significant in only the 2018 holiday model, with its marginal effect decreasing the likelihood of minor injury and increasing that of severe and fatal injuries. Although temporal instability of intersection effect on motorcyclist injury was observed (i.e., insignificant in some models), all time-of-year models had the consistent results showing that motorcycle crashes within the intersections area had higher probability of severe and fatal injuries. Possible explanation may be attributed to the high vulnerabilities of the motorcycle at the intersection due to the increases in riders' risks as well as their exposures (e.g., right-angle crash exposures, risks from turning manoeuvres, failure of other vehicle drivers to observe a motorcycle and judge correctly the speed/distance of an oncoming motorcycle, road side conflicts due to stopping/waiting vehicles, and dangerous interactions with opposing traffic (Haque et al., 2008, 2012; Haque and Chin, 2010)).

The variable pertaining to crashes within 100 m from U-turns was statistically significant in the 2016 and 2019 weekday models, with the marginal effect increasing the likelihood of severe injury (**Table 4.10**). For weekend crashes, this indicator was significant in the 2016, 2018, and 2019 models, with the average marginal effects increasing severe injury probability in the 2016 and 2018 models and increasing fatal injury probability in the 2019 model (**Table 4.10-4.11**). In the holiday model, this indicator was significant only in the 2018 model, with the marginal effect increasing the likelihood of minor and fatal injury (**Table 4.9-4.11**). Again, all time-of-year models had the consistent findings showing that motorcyclists had higher probability of severe or fatal injury (particularly in recent period 2018 and 2019) when involving in crashes with U-turn area. Possible reasons may be attributed to riders' exposures to dangerous conflicts such as cross- and weaving conflicts that encourage dangerous crash type such as angle- or right-angle collision with oncoming traffic (Se et al., 2021a).

The variable reflecting crashes on bridges increased the likelihood of motorcyclist fatal injury in the 2016 weekend and 2017 weekday models (**Table 4.11)**, and increased the likelihood of severe injury in the 2017 holiday and 2018 weekend models (**Table 4.10)**. Despite temporal instability, all time-of-year models seem to have consistent findings regarding motorcycle crashes on bridge sections. Possible reasons may be attributed to higher crash impacts due to collision (either head-on or sideswipe) with other vehicles on the bridge, or the possibility that riders may fall off the bridge due to their initial reaction to avoid potential collision with other vehicles, or riders hit the handrail of the bridge which can be treated as fixed object and subsequently increase injury severity level (Islam, 2021; Shaheed and Gkritza, 2014)

The variable indicating crashes in urban areas (versus rural areas) was statistically significant in all periods from the 2016 to 2019 weekday models, with the average marginal effects increasing the likelihood of minor injury (**Table 4.9**). For weekend crashes, this indicator was significant in the 2016, 2017, and 2019 models, with the marginal effects decreasing the likelihood of fatal injury in the 2016 and 2019 models and increasing that of severe injury in the 2017 model (**Table 4.10-4.11**). However, this variable was significant only in the 2017 and 2018 holiday models, with the average marginal effects increasing the likelihood of minor injury in the 2017 model (**Table 4.9**) and decreasing that of fatal injury in the 2019 model (**Table 4.11**). Overall, motorcycle crashes in urban areas were less severe than those in rural areas for numerous reasons, such as lower speed limits, dense traffic volumes (which discourage operating motorcycles at high speed), better quality/proximity to hospital centers, and higher intention to use safety helmet of urban riders (Kashani et al., 2014; Se et al., 2021a; Champahom et al., 2020c; Jomnonkwao et al., 2020).

4.7.4 Environment- and temporal-related characteristics

The variable pertaining to motorcycle crashes on wet roads was statistically significant in only some of the weekday and weekend models and not in the holiday models. As indicated in **Table 4.10-4.11**, their average marginal effect showed an increase of likelihood of severe and fatal injuries (2017 weekday, 2018 weekday, 2016 weekend and 2018 weekend models). Conversely, the variable reflecting motorcycle crashes under rainy conditions was statistically significant in the

2018 and 2019 weekend models and the 2018 holiday model with the average marginal effects increasing the likelihood of minor injury in the weekend models and minor/severe injury in the holiday model (**Table 4.9-4.10**). Possible explanation may be attributed to the possibility that bad weathers could act as a disincentive against risk-seeking behaviors (e.g., speeding, aggressive driving, dangerous overtaking, etc.) and subsequently reduce crash severity level (Pai and Saleh, 2007; Vajari et al., 2020). On the other hand, motorcyclists may be more likely to carelessly ride under clear weather (e.g., speeding), or (in case of riding on wet road) riders tend to increase the speed to compensate the time loss from waiting for the rain to stop or riding at low speed under raining condition, which may consequently lead to an increase in the crash severity level.

Regarding the lighting system, the variable reflecting motorcycle crashes on lit roads was statistically significant in the 2017 and 2019 weekday models and the 2016 and 2018 holiday models, with overall marginal effects increasing the likelihood of fatal injury (**Table 4.11**). Likewise, the variable pertaining to motorcycle crashes on unlit roads was statistically significant in all periods (2016 holiday, 2017 weekday and holiday, 2018 weekday, weekend and holiday and 2019 weekday and weekend models), with general agreement of marginal effects increasing the probability of severe or fatal injury (**Table 4.10-4.11**). Although motorcycle crashes on both lit and unlit roads had a higher probability of sustaining severe and fatal injuries (given that the crashes occur during nighttime), the unlit-road indicator was found significant in eight models whereas the lit-road indicator was significant in only four out of twelve models. This clearly indicates that at least riding on lit roads did not produce a significant risk of being seriously injured or killed in the crashes as much as riding on unlit roads. Although insignificant in some models, these two indicators seem to affect the motorcyclist injury severity equally regardless of time-of-year. Similar findings were also reported by existing literature (Chang et al., 2016; Jou et al., 2012; Shaheed and Gkritza, 2014).

The variable indicating motorcycle crashes between midnight and early morning was statistically significant in most of the models including the 2016 to 2019 weekday, 2016 and 2017 weekend, and the 2016, 2018, and 2019 holiday models. This indicator showed, in general, a stable effect across all significant models with their average marginal effects increasing the likelihood of fatal injury (**Table 4.11**). Again, regardless of time-of-year, motorcycle crashes between midnight to early morning had higher probability of motorcyclists sustaining fatal injury, which may be due to low visibility, speeding (due to low traffic volume) or physical conditions of the riders (being drunk or fatigued). This finding is fairly intuitive and consistent with numerous previous studies (Islam, 2021; Vajari et al., 2020, Se et al., 2021a).

Regarding time-of-day, the variable reflecting motorcycle crashes during peak hours was statistically significant in the 2016 weekday model (with the effect increasing the likelihood of severe injury (**Table 4.10**)) and 2018 and 2019 holiday models (with the stable marginal effects increasing the likelihood of fatal injury (**Table 4.11**)). Lastly, the variable pertaining to motorcycle crashes during evenings was statistically significant in the 2017 weekend and the 2016, 2018, and 2019 holiday models with their average marginal effects increasing the likelihood of fatal injury (**Table 4.11**). While the findings are in line with the past study (Islam and Brow, 2017), these time-of-day's findings differentiate the effect of holiday crashes on motorcyclist injury from weekday and weekend crashes. These findings indicated the need to pay more attention to improving motorcyclist safety during the two holidays, particularly during peak-hour and evening to midnight periods. However, in general without mentioning the time-of-year, other studies reported that motorcycle crashes during peak-hour decreased injury severity (Ijaz et al., 2021), whereas non-peak-hour crashes tend to increase motorcycle crashes injury severity (Jung et al., 2013). The results of this study help uncover the heterogeneous effects of these indicators that may vary across time-of-year.

4.7.5 Crash-related characteristics

The variable reflecting riders hitting other motorcycles was statistically significant in all weekday models, weekend models, and 2017 and 2019 holiday models with the stable average marginal effects (in majority) increasing the likelihood of minor or severe injury (**Table 4.9-4.10**). Possible explanation is that collisions between two motorcycles may generate less crash impact compared to collisions between motorcycle and vehicles. This finding is also supported by existing studies (De lapperent, 2006; Wassem et al., 2019; Se et al., 2021a).

The indicator for riders hitting passenger cars was statistically significant in three weekday models with the average marginal effects increasing the likelihood of severe injury in the 2016 and 2017 models and fatal injury only in the 2019 model (**Table 4.10-4.11**). For weekend crashes, this indicator was significant in the 2018 and 2019 models with the marginal effects increasing the likelihood of fatal injury in 2018 and severe injury in 2019 (**Table 4.10-4.11**). Additionally, this indicator was found to increase the likelihood of fatal injury in the 2016 and 2018 holiday models (and decrease that of minor and severe injury probabilities). Overall, the effect of hitting passenger cars was more serious during the two holidays than weekends and weekdays. Likewise, regardless of time-of-year models, the indicator pertaining to riders hitting pickup-trucks, van, minibus, and large-truck were found statistically significant in various year models, with the consistent and stable average marginal effects increasing the likelihood of fatal injury (**Table 4.11**). These findings are intuitive since such collision mechanisms between motorcycle and larger-sized vehicles are more likely to result in high impact crashes which consequently increase the resulting injury severity level. In addition, the findings are also supported by numerous past studies (Ijaz et al., 2021; Se et al., 2021a; Jung et al., 2013; Rifaat et al., 2012; Shaheed et al., 2013; Li et al., 2021a, 2021b)

As shown in **Table 4.10-4.11**, the indicator for riders involved in rear-end crashes was statistically significant in the 2017 weekend model (increasing the likelihood of fatal injury), 2019 weekday model (increasing the likelihood of severe injury) and 2017 and 2018 holiday models (increasing the likelihood of severe injury). The indicator reflecting riders involved in side-swipe crashes was statistically significant in the 2016, 2018, and 2019 weekday models (increasing the probability of minor and severe injury in the 2016 and 2019 models, and minor and fatal injury in the 2018 model), 2016 and 2018 weekend models (increasing the likelihood of minor injury), and 2016 and 2018 holiday models (increasing the likelihood of severe and fatal injuries, respectively). The indicator pertaining to riders involved in single-motorcycle crashes was statistically significant in the 2016, 2017 2018 weekday models (increasing the likelihood of severe and fatal injuries), 2016 weekend model (increasing the likelihood of severe injury), 2016 and 2019 holiday (increasing the likelihood of minor injury). Regarding these crash types, both temporal instability and nontransferability between time-of-year models were observed. This may be attributed to numerous important source of variability (such as crash configurations relative to the vehicle path of origin that is unknown and a limitation of the current study). Pai and Saleh (2007) provided an example that could be used for explanation. That is, it is difficult to differentiate between side-swipe or rear-end crashes using the crash configuration (provided by the officer and entirely subjected to their judgment) since both types are the same-direction collision (collision between one motorcycle and one vehicle traveling from the same direction). In addition, numerous other factors may also have (varied-) influences on the severity level (or frequency of the crash) of rear-end, sideswipe or angle motorcycle crashes including controlled/uncontrolled intersections/junctions, another vehicle direction, stop signs, give-way signs, markings, pre-crash manoeuvres by vehicles and motorcycles, motorcycle's right of way violation, shoulder width, lane number, and availability of footpath shoulders (Pai and Saleh, 2008; Champahom et al., 2020b). Another potential source of variability may be attributed to whether the rider is at-fault or not-at-fault (Haque et al., 2009). For example, if a rider is not-at-fault and got rear-ended (or even sideswiped) by a vehicle from the back, the rider is likely to be ejected or tumble, and consequently more likely to sustain a serious injury (Pai and Saleh, 2007). This is also a limitation of the current paper. It would be fruitful for future work to attempt to collect a more comprehensive dataset and address these limitations while also considering possible temporal instability.

The indicator reflecting riders involved in head-on crashes was statistically significant in the 2016, 2018, and 2019 weekday models; the 2017 and 2019 weekend models; and the 2018 to 2019 holiday models with the consistent marginal effects, regardless of time-of-year, increasing the likelihood of fatal injury and decreasing that of minor and severe injuries (**Table 4.9-4.11**). This finding is fairly logical and supported by numerous literature (Schneider and Savolainen, 2011; Jung et al., 2013; Li et al., 2021b; Chang et al., 2021; Se et al., 2021a). With relatively high fatal injury marginal effect of the head-on crash variable compared to other variables, additional attention is required in order to reduce head-on crashes involving motorcycle users.

4.8 Instability Assessment with Predictive Comparison

As shown in **Tables 4.9–4.11** and discussed in the previous section, the factors affecting motorcyclist injury severities and the effects of significant factors on injury severity probabilities changed across time-of-year models and across years. To explore this issue further, this study performed an out-of-sample prediction simulation to answer these fundamental questions: (1) What would have been the injury severity distribution for weekend or holiday motorcycle crashes if weekday estimated model parameters (based on weekday data) were used to forecast them? (2) What would have been the injury severity distribution for holiday motorcycle crashes if weekend estimated model parameters (based on weekend data) were used to forecast them? (3) And what would have been the injury severity distribution for the later-year crashes if previous-year estimated model parameters (based on the previous-year data) were used to forecast them (for each time-of-year model)? Answering these questions would help determine the aggregate effect of the observed shift in the influence of explanatory variables on injury severity probability across time-of-year models and yearly models.

Computationally, this out-of-sample prediction can be achieved by simulation, numerically integrating equation (2) in section 3 to compute individual crash injury severity probabilities. It should be noted that these out-of-sample forecasts do not simply use the mean of the random parameters, which would result in obviously biased predictions (i.e., the full distribution of random parameters [estimated means and variances] must be unutilized in the simulation process). For details regarding this technique and how to interpret the results, reader may refer to recent studies on injury severity (Alnawmasi and Mannering, 2022; Alogaili and Mannering, 2020, 2022; Hou et al., 2022; Islam et al., 2020).

Table 4.9 Summary of minor injury marginal effects

	2016			2017			2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Rider characteristic/actions												
Male (1 if rider was male, 0 female)	-	-	-0.0340	-	-	-	-	-	-0.0384	-	-	-0.0557
Pillion (1 if there was/were pillion(s), 0 otherwise)	-	-0.0212	-0.0004	-0.0125	-0.0390	-0.0097	-	-	-0.0123	-0.0265	-0.0198	-0.0124
Speeding (1 if rider was speeding, 0 otherwise)	-	-	-	0.0371	-	0.0066	-	0.1068	-0.0664	-0.0353	0.0434	-
Hit unexpected crossing object (1 if rider hit an unexpected crossing object, 0 otherwise)	-	-0.0016	-	-	0.0194	-	-	-	-0.0297	-0.0101	0.0133	-
Overtake (1 if rider overtook improperly, 0 otherwise)	-	-	-	-	-	-	-	-	-0.0046	-0.0015	-	-
Alcohol (1 if rider was under influence of alcohol, 0 otherwise)	-0.0019	-	-	-	-	-	-	-0.0008	-	-	0.0035	0.0050
Fatigued (1 if rider was fatigued, 0 otherwise)	-	0.0021	-	-0.0012	-	-0.0021	-	-	-	-	-	-0.0020
Roadways attributes												
Main lane (1 if crash occurred on main lane, 0 otherwise)	-0.0073	-	-	-0.0041	-	-	-	-	-	-	-	-0.0044
Frontage lane (1 if crash occurred on frontage lane, 0 otherwise)	-0.0047	-	-	0.0046	0.0071	-0.0022	0.0044	0.0062	-	-	-	-0.0033
Work zone (1 if crash occurred on work zone, 0 otherwise)	-	-	-	-	-0.0041	-	-	0.0019	-	-	-	-
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise)	-	-0.0355	-	-0.0237	-0.0393	-	-0.0579	-0.0095	-	-0.0459	-0.0259	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise)	-0.0404	-0.0643	-0.0549	-0.0200	-0.0595	-	-0.0450	-0.0745	-	-	-0.0373	-
Undivided median (1 if crash occurred on undivided road, 0 otherwise)	-	-	-	-	-	-	-	-	-	-0.0290	-	-
Flush median (1 if crash occurred on flush median road, 0 otherwise)	-	-	-	-	-	-	-	-0.0152	-	-	-	-

Table 4.9 Summary of minor injury marginal effects (Cont.)

	2016			2017			2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Raised median (1 if crash occurred on raised median road, 0 otherwise)	-	-	-	0.0092	-	-	-	-	-	-	0.0049	-
Depressed median (1 if crash occurred on depressed median road, 0 otherwise)	-	-	-	-0.0094	-	-	-0.0253	-0.0223	-	-	-	-
Barrier median (1 if crash occurred on barrier median road, 0 otherwise)	-	0.0270	-	0.0182	0.0259	-	-0.0024	-	-	0.0092	-	-
concrete pavement (1 if crash occurred on Concrete pavement road, 0 otherwise)	-	-	-0.0120	0.0089	0.0142	-	0.0092	-	0.0094	0.0109	-	-
Curve (1 if crash occurred on curve road, 0 otherwise)	-0.0083	-	-	-0.0061	-	-0.0103	-	-0.0052	0.0074	-0.0042	-	-
Grade (1 if crash occurred on graded road, 0 otherwise)	-0.0014	-0.0023	-	-	-0.0039	-	-0.0041	-	-	-	-	-
Intersection (1 if crash occurred within 100m from intersection, 0 otherwise)	-0.0079	-	-	-0.0059	-0.0084	-	-0.0120	-0.0093	-0.0083	-	-	-
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise)	-0.0030	-0.0117	-	-	-	-	-	0.0051	0.0053	-0.0045	-0.0086	-
Bridge (1 if crash occurred on the bridge, 0 otherwise)	-	-0.0019	-	-0.0014	-	-0.0007	-	-0.0010	-	-	-	-
Urban (1 if crash occurred in urban road, 0 rural)	0.0217	0.0104	-	0.0165	-0.0016	0.0134	0.0110	-	0.0065	0.0067	0.0122	-
Environmental and temporal characteristics												
Wet road (1 if crash occurred on wet road, 0 otherwise)	-	-0.0162	-	-0.0082	-	-	-0.0150	-0.0131	-	-	-	-
Rain (1 if crash occurred under rainy condition, 0 otherwise)	-	-	-		-	-	-	0.0100	-0.0038	-	0.0128	-
Lit road (1 if crash occurred on lit road, 0 otherwise)	-	-	-0.0372	-0.0265	-	-	-	-	-0.0228	-0.0313	-	-

Table 4.9 Summary of minor injury marginal effects (Cont.)

	2016			2017			2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Unlit road (1 if crash occurred on unlit road, 0 otherwise)	-	-	-0.0172	-0.0100	-	-0.0311	-0.0116	-0.0219	-0.0155	-0.0161	-0.0146	-
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise)	-0.0097	-0.0126	0.0118	-0.0142	-0.0171	-	-0.0193	-	-0.0190	-0.0158	-	-0.0391
Peak hours (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise)	-0.0015	-	-	-	-	-	-	-	-0.0112	-	-	-0.0070
Evening (1 if crash occurred between 18:00-23:59, 0 otherwise)	-	-	0.0193	-	-0.0295	-	-	-	-0.0119	-	-	-0.0160
Crash characteristics												
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise)	0.0099	0.0172	-	0.0091	0.0110	0.0123	0.0050	0.0110	-	0.0097	0.0105	0.0074
Hit passenger car (1 if rider hit passenger car, 0 otherwise)	0.0145	-	-0.0174	-0.0114	-	-	-	0.0358	-0.0176	0.0157	0.0165	-
Hit pickup truck (1 if rider hit pickup truck,0 otherwise)	-0.0110	-	-0.0247	-	-	-0.0124	-0.0153	-	-0.0195	-	-	-0.0137
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise)	-	-0.0104	-0.0050	-	-	-0.0044	-0.0045	-	-0.0089	-0.0045	-	-
Hit truck (1 if rider hit large truck, 0 otherwise)	-0.0143	-0.0124	-	-0.0072	-0.0170	-0.0040	-0.0142	-0.0099	-0.0083	-0.0236	-0.0166	-0.0044
Rear-end (1 if type was rear-end crash, 0 otherwise)	-	-	-		-0.0199	-0.0102			0.0061	0.0245	-	-
Side-swipe (1 if type was side-swipe crash, 0 otherwise)	0.0109	0.0118	0.0085	-	-	-	0.0115	0.0486	-0.0014	0.0251	-	-
Single-crash (1 if type was single-crash crash, 0 otherwise)	-0.0064	-0.0068	0.0176	-0.0003	-	-	0.0043	-	-	-	-	0.0421
Head-on (1 if type was head-on crash, 0 otherwise)	-0.0028	-	-	-	-0.0087	-0.0084	-0.0141	-	-0.0060	-0.0071	-0.0111	-0.0044

Table 4.10 Summary of severe injury marginal effect

	2016			2017			2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Rider characteristic/actions												
Male (1 if rider was male, 0 female)	-	-	0.0424	-	-	-	-	-	-0.0224	-	-	0.0355
Pillion (1 if there was/were pillion(s), 0 otherwise)	-	-0.0110	-0.0010	-0.0072	-0.0183	-0.0069	-	-	-0.0078	-0.0133	-0.0092	-0.0064
Speeding (1 if rider was speeding, 0 otherwise)	-	-	-	-0.0171	-	-0.0031	-	-0.0390	-0.0421	-0.0178	-0.0191	-
Hit unexpected crossing object (1 if rider hit a unexpected crossing object, 0 otherwise)	-	0.0030	-	-	0.0107	-	-	-	-0.0174	-0.0046	0.0073	-
Overtake (1 if rider overtook improperly, 0 otherwise)	-	-	-	-	-	-	-	-	-0.0029	-0.0009	-	-
Alcohol (1 if rider was under influence of alcohol, 0 otherwise)	0.0006	-	-	-	-	-	-	0.0045	-	-	0.0025	0.0034
Fatigued (1 if rider was fatigued, 0 otherwise)	-	-0.0001	-	-0.0011	-	-0.0013	-	-	-	-	-	0.0026
Roadways attributes												
Main lane (1 if crash occurred on main lane, 0 otherwise)	0.0090	-	-	0.0058	-	-	-	-	-	-	-	0.0058
Frontage lane (1 if crash occurred on frontage lane, 0 otherwise)	0.0058	-	-	0.0011	0.0014	-0.0012	0.0020	0.0036	-	-	-	0.0017
Work zone (1 if crash occurred on work zone, 0 otherwise)	-	-	-	-	0.0073	-	-	0.0019	-	-	-	-
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise)	-	-0.0199	-	0.0385	-0.0250	-	0.0203	-0.0036	-	-0.0245	-0.0120	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise)	0.0201	-0.0360	0.0266	0.0350	-0.0293	-	0.0143	-0.0477	-	-	-0.0174	-
Undivided median (1 if crash occurred on undivided road, 0 otherwise)	-	-	-	-	-	-	-	-	-	-0.0174	-	-
Flush median (1 if crash occurred on flush median road, 0 otherwise)	-	-	-	-	-	-	-	0.0094	-	-	-	-

Table 4.10 Summary of severe injury marginal effect (Cont.)

	2016			2017			2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Raised median (1 if crash occurred on raised median road, 0 otherwise)	-	-	-	0.0046	-	-	-	-	-	-	0.0031	-
Depressed median (1 if crash occurred on depressed median road, 0 otherwise)	-	-	-	0.0046	-	-	0.0107	0.0111	-	-	-	-
Barrier median (1 if crash occurred on barrier median road, 0 otherwise)	-	-0.0183	-	-0.0088	-0.0181	-	0.0025	-	-	-0.0038	-	-
Concrete pavement (1 if crash occurred on concrete pavement road, 0 otherwise)	-	-	0.0157	-0.0039	-0.0093	-	-0.0035	-	-0.0105	-0.0046	-	-
Curve (1 if crash occurred on curve road, 0 otherwise)	0.0038	-	-	-0.0048	-	0.0064	-	0.0140	-0.0082	0.0085	-	-
Grade (1 if crash occurred on graded road, 0 otherwise)	-0.0013	0.0070	-	-	-0.0018	-	0.0015	-	-	-	-	-
Intersection (1 if crash occurred within 100m from intersection, 0 otherwise)	0.0040	-	-	0.0090	0.0128	-	0.0045	0.0188	0.0069	-	-	-
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise)	0.0034	0.0053	-	-	-	-	-	0.0026	-0.0060	0.0068	-0.0046	-
Bridge (1 if crash occurred on the bridge, 0 otherwise)	-	-0.0017	-	-0.0006	-	0.0014	-	0.0038	-	-	-	-
Urban (1 if crash occurred in urban road, 0 rural)	-0.0101	0.0049	-	-0.0080	0.0018	-0.0082	0.0049		0.0039	-0.0099	0.0048	-
Environmental and temporal characteristics												
Wet road (1 if crash occurred on wet road, 0 otherwise)	-	-0.0078	-	0.0041	-	-	0.0049	-0.0026	-	-	-	-
Rain (1 if crash occurred under rainy condition, 0 otherwise)	-	-	-	-	-	-	-	-0.0017	0.0046	-	-0.0053	-
Lit road (1 if crash occurred on lit road, 0 otherwise)	-	-	0.0185	-0.0123	-	-	-	-	0.0186	-0.0132	-	-

Table 4.10 Summary of severe injury marginal effect (Cont.)

	2016			2017			2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Unlit road (1 if crash occurred on unlit road, 0 otherwise)	-	-	0.0229	-0.0061	-	0.0196	-0.0059	0.0081	0.0128	-0.0084	-0.0060	-
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise)	-0.0053	-0.0033	-0.0160	-0.0066	-0.0067	-	-0.0084	-	-0.0135	-0.0072	-	-0.0192
Peak hours (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise)	0.0030	-	-	-	-	-	-	-	-0.0057	-	-	-0.0042
Evening (1 if crash occurred between 18:00-23:59, 0 otherwise)	-	-	-0.0269	-	-0.0172	-	-	-	-0.0094	-	-	-0.0097
Crash characteristics												
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise)	0.0052	-0.0069	-	0.0047	0.0054	-0.0076	0.0024	0.0079	-	0.0053	0.0048	-0.0115
Hit passenger car (1 if rider hit passenger car, 0 otherwise)	0.0072	-	-0.0092	0.0175	-	-	-	-0.0124	-0.0104	-0.0075	0.0078	-
Hit pickup truck (1 if rider hit pickup truck,0 otherwise)	-0.0061	-	-0.0116	-	-	-0.0086	0.0056	-	-0.0127	-	-	-0.0089
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise)	-	0.0064	-0.0023	-	-	-0.0029	0.0018	-	-0.0052	0.0021	-	-
Hit truck (1 if rider hit large truck, 0 otherwise)	-0.0039	-0.0064	-	-0.0025	-0.0077	-0.0033	-0.0051	-0.0049	-0.0051	-0.0123	-0.0069	-0.0026
Rear-end (1 if type was rear-end crash, 0 otherwise)	-	-	-	-	-0.0101	0.0152	-	-	0.0038	0.0122	-	-
Side-swipe (1 if type was side-swipe crash, 0 otherwise)	0.0041	0.0076	0.0038	-	-	-	-0.0197	-0.0176	-0.0005	0.0118	-	-
Single-crash (1 if type was single-crash crash, 0 otherwise)	0.0043	0.0119	-0.0221	0.0024	-	-	-0.0078	-	-	-	-	-0.0266
Head-on (1 if type was head-on crash, 0 otherwise)	0.0045	-	-	-	-0.0043	-0.0045	-0.0081	-	-	0.0029	-0.0055	-0.0028

Table 4.11 Summary of fatal injury marginal effects

	2016			2017			2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Rider characteristic/actions												
Male (1 if rider was male, 0 female)	-	-	-0.0083	-	-	-	-	-	0.0608	-	-	0.0202
Pillion (1 if there was/were pillion(s), 0 otherwise)	-	0.0322	0.0013	0.0197	0.0573	0.0166	-	-	0.0201	0.0399	0.0291	0.0187
Speeding (1 if rider was speeding, 0 otherwise)	-	-	-	-0.0200		-0.0035	-	-0.0677	0.1085	0.0531	-0.0243	-
Hit unexpected crossing object (1 if rider hit an unexpected crossing object, 0 otherwise)	-	-0.0014	-	-	-0.0302	-	-	-	0.0471	0.0147	-0.0206	-
Overtake (1 if rider overtook improperly, 0 otherwise)	-	-	-	-	-	-	-	-	0.0075	0.0024	-	-
Alcohol (1 if rider was under influence of alcohol, 0 otherwise)	0.0013	-	-	-	-	-	-	-0.0037	-	-	-0.0060	-0.0084
Fatigued (1 if rider was fatigued, 0 otherwise)	-	-0.0020	-	0.0023	-	0.0035	-	-	-	-	-	-0.0006
Roadways attributes												
Main lane (1 if crash occurred on main lane, 0 otherwise)	-0.0017	-	-	-0.0017	-	-	-	-	-	-	-	-0.0014
Frontage lane (1 if crash occurred on frontage lane, 0 otherwise)	-0.0012	-	-	-0.0057	-0.0086	0.0034	-0.0064	-0.0098	-	-	-	0.0016
Work zone (1 if crash occurred on work zone, 0 otherwise)	-	-	-	-	-0.0032	-	-	-0.0039	-	-	-	-
Four lanes (1 if crash occurred on four-lanes road, 0 otherwise)	-	0.0554	-	-0.0148	0.0643	-	0.0376	0.0131	-	0.0704	0.0379	-
Two lanes (1 if crash occurred on two-lanes road, 0 otherwise)	0.0203	0.1002	0.0283	-0.0150	0.0887	-	0.0307	0.1222	-	-	0.0547	-
Undivided median (1 if crash occurred on undivided road, 0 otherwise)	-	-	-	-	-	-	-	-	-	0.0464	-	-
Flush median (1 if crash occurred on flush median road, 0 otherwise)	-	-	-	-	-	-	-	0.0058	-	-	-	-

Table 4.11 Summary of fatal injury marginal effects (Cont.)

	2016			2017			2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Raised median (1 if crash occurred on raised median road, 0 otherwise)	-	-	-	-0.0138	-	-	-	-	-	-	-0.0080	-
Depressed median (1 if crash occurred on depressed median road, 0 otherwise)	-	-	-	0.0048	-	-	0.0146	0.0111	-	-	-	-
Barrier median (1 if crash occurred on barrier median road, 0 otherwise)	-	-0.0087	-	-0.0094	-0.0079	-	-0.0001	-	-	-0.0054	-	-
Concrete pavement (1 if crash occurred on concrete pavement road, 0 otherwise)	-	-	-0.0036	-0.0049	-0.0049		-0.0057		0.0011	-0.0063	-	-
Curve (1 if crash occurred on curve road, 0 otherwise)	0.0045	-	-	0.0109		0.0039		-0.0088	0.0009	-0.0042	-	-
Grade (1 if crash occurred on graded road, 0 otherwise)	0.0027	-0.0047	-	-	0.0057	-	0.0026	-	-	-	-	-
Intersection (1 if crash occurred within 100m from intersection, 0 otherwise)	0.0038	-	-	-0.0032	-0.0044	-	0.0075	-0.0094	0.0014	-	-	-
U-turn (1 if crash occurred within 100m from U-turn, 0 otherwise)	-0.0004	0.0064	-	-	-	-	-	-0.0077	0.0007	-0.0023	0.0132	-
Bridge (1 if crash occurred on the bridge, 0 otherwise)	-	0.0035	-	0.0020	-	-0.0007	-	-0.0029	-	-	-	-
Urban (1 if crash occurred in urban road, 0 rural)	-0.0116	-0.0153	-	-0.0085	-0.0002	-0.0052	-0.0159	-	-0.0104	0.0032	-0.0171	-
Environmental and temporal characteristics												
Wet road (1 if crash occurred on wet road, 0 otherwise)	-	0.0241	-	0.0041	-	-	0.0101	0.0157	-	-	-	-
Rain (1 if crash occurred under rainy condition, 0 otherwise)	-	-	-	-	-	-	-	-0.0084	-0.0008	-	-0.0074	-
Lit road (1 if crash occurred on lit road, 0 otherwise)	-	-	0.0187	0.0388	-	-	-	-	0.0042	0.0445	-	-

Table 4.11 Summary of fatal injury marginal effects (Cont.)

	2016			2017			2018			2019		
	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
Unlit road (1 if crash occurred on unlit road, 0 otherwise)	-	-	-0.0057	0.0161	-	0.0115	0.0175	0.0138	0.0028	0.0245	0.0206	-
Midnight/early morning (1 if crash occurred between 00:00 - 6:59, 0 otherwise)	0.0150	0.0159	0.0041	0.0208	0.0238	-	0.0277	-	0.0325	0.0230	-	0.0583
Peak hours (1 if crash occurred between 7:00-8:59 and 16:00:17:59, 0 otherwise)	-0.0016	-	-	-	-	-	-	-	0.0169	-	-	0.0112
Evening (1 if crash occurred between 18:00-23:59, 0 otherwise)	-	-	0.0076	-	0.0467	-	-	-	0.0213	-	-	0.0258
Crash characteristics												
Hit motorcycle (1 if rider hit other motorcycle, 0 otherwise)	-0.0151	-0.0102	-	-0.0138	-0.0164	-0.0047	-0.0074	-0.0189	-	-0.0149	-0.0153	0.0041
Hit passenger car (1 if rider hit passenger car, 0 otherwise)	-0.0218	-	0.0265	-0.0061	-	-	-	-0.0233	0.0281	-0.0082	-0.0243	-
Hit pickup truck (1 if rider hit pickup truck,0 otherwise)	0.0171	-	0.0363	-	-	0.0210	0.0097	-	0.0321	-	-	0.0227
Hit van/minibus (1 if rider hit van or minibus, 0 otherwise)	-	0.0040	0.0073	-	-	0.0073	0.0027	-	0.0141	0.0023	-	-
Hit truck (1 if rider hit large truck, 0 otherwise)	0.0182	0.0188	-	0. 0097	0.0248	0.0073	0.0193	0.0148	0.0134	0.0359	0.0235	0.0069
Rear-end (1 if type was rear-end crash, 0 otherwise)	-	-	-	-	0.0300	-0.0050	-	-	-0.0099	-0.0367	-	-
Side-swipe (1 if type was side-swipe crash, 0 otherwise)	-0.0149	-0.0194	-0.0123	-	-	-	0.0082	-0.0310	0.0020	-0.0370	-	-
Single-crash (1 if type was single-crash crash, 0 otherwise)	0.0021	-0.0051	0.0045	-0.0021	-	-	0.0034	-	-	-	-	-0.0154
Head-on (1 if type was head-on crash, 0 otherwise)	-0.0018	-	-	-	0.0131	0.0129	0.0222	-	0.0013	0.0042	0.0166	0.0072

Table 4.12 Summary of change in motorcyclist injury severity prediction means between weekday, weekend and holiday by year.

Year	Injury	Weekdays predict weekends	Weekdays predict holidays	Weekends predict holidays
2016	Minor	0.0764	-0.0404	-0.0290
	Severe	-0.1350	-0.1547	-0.1684
	Fatal	0.0585	0.1950	0.1974
2017	Minor	0.1553	-0.0177	-0.1842
	Severe	-0.1011	-0.1637	-0.1883
	Fatal	-0.0541	0.1814	0.3725
2018	Minor	0.0842	-0.0081	-0.1782
	Severe	0.0549	-0.1322	-0.2129
	Fatal	-0.1391	0.1403	0.3912
2019	Minor	0.0810	-0.1041	-0.0816
	Severe	-0.0244	-0.1286	-0.1196
	Fatal	-0.0565	0.2327	0.2013

The study begins by comparing time-of-year crashes (i.e., to answer questions 1 and 2). The results of this out-of-sample simulation are presented in **Table 4.12**, which summarizes the changes in motorcyclist injury severity prediction means between weekday models predicting weekend crashes, weekday models predicting holiday crashes, and weekend models predicting holiday crashes in all years from 2016 to 2019. First, examining the use of weekday models (i.e., using weekday data to initially estimate the model) to predict weekend injury severity given the observed weekend crash characteristics (i.e., observation sample that was not used for model estimation), **Table 4.12** shows that minor injury differences are relatively stable (in terms of direction but not magnitude) and severe and fatal injuries differences are unstable from 2016 to 2019. Specifically, using the weekday model to predict the weekend crashes overestimates minor injury by 0.0764, 0.1553, 0.0842, and 0.0810 from 2016 to 2019, respectively. Using the same formulation, severe injury predictions are underestimated

Table 4.13 Summary of change in motorcyclist injury severity prediction means between year of crash by time-of-year.

Base year	Injury	Forecast year								
		2017			2018			2019		
		Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays	Weekdays	Weekends	Holidays
2016	Minor	0.0525	0.1242	-0.0278	0.0424	0.2014	0.1338	0.0642	0.1309	-0.0824
	Severe	-0.0414	-0.0120	0.0512	-0.0040	-0.0211	-0.0161	-0.0243	-0.0404	0.0960
	Fatal	-0.0111	-0.1122	-0.0233	-0.0384	-0.1803	-0.1178	-0.0399	-0.0906	-0.0135
2017	Minor	-	-	-	0.0995	0.0661	0.0928	0.1120	-0.0283	-0.0803
	Severe	-	-	-	-0.0131	0.0256	-0.0314	-0.0605	-0.0555	0.1082
	Fatal	-	-	-	-0.0864	-0.0917	-0.0614	-0.0515	0.0838	-0.0279
2018	Minor	-	-	-	-	-	-	0.1054	-0.0363	-0.0722
	Severe	-	-	-	-	-	-	-0.0781	-0.0336	0.0515
	Fatal	-	-	-	-	-	-	-0.0273	0.0699	0.0207

in 2016, 2017, and 2019 by 0.1350, 0.1011, and 0.0244, respectively, but overestimated in 2018 by 0.0549. Fatal injury predictions are overestimated in 2016 by 0.0585 and underestimated in 2017, 2018, and 2019 by 0.0541, 0.1391, and 0.0565, respectively. Second, using the weekday or weekend model to predict holiday injury severity would underestimate minor and severe injury but overestimate fatal injury in all years from 2016 to 2019. Thus, if the explanatory variables were the same in each crash that occurred during holidays, either weekday or weekend estimated parameters would predict fewer minor and severe crashes and more fatal crashes. Simply put, compared to holiday crashes, weekday or weekend crashes would have expected fewer minor injuries, much fewer severe injuries and more fatal injuries for motorcyclists.

Next, to further investigate the aggregate effect of temporal instability on each time-of-year model, **Table 4.13** presents a summary of changes in motorcyclist injury severity prediction means across years by weekday, weekend, and holiday while using the 2016 to 2018 models as base years. The results show that the 2016 weekday model overestimated minor injury in all subsequent years and underestimated severe and fatal injuries (similar to when 2017 weekday and 2018 weekday were used as base models). For weekend crashes, the 2016 model estimates also expected more minor injuries and fewer severe and fatal injuries in all subsequent-year crashes. However, using 2017 weekend as the base year underestimated only fatal injury (while overestimating minor and severe injuries) in 2018 weekend crashes and overestimated fatal injury in 2019 weekend crashes (while underestimating minor and severe injuries). Likewise, the 2018 weekend model (as the base year) underestimated minor and severe injuries while overestimating fatal injury in 2019 weekend crashes. Regarding holiday crashes, injury severity prediction differences were relatively unstable from 2016 to 2019. Using the 2016 holiday model (as the base model) to predict 2017 and 2019 holiday crashes overestimated severe injury (while underestimating minor and fatal injuries), and predicting 2018 holiday crashes overestimated minor injury (while underestimating severe and fatal injuries). Using the 2017 holiday model estimate to predict 2018 holiday crashes overestimated minor injury (while underestimating severe and fatal injuries), and to forecast 2019 holiday crashes overestimated severe injury (while predicting fewer minor and fatal injuries). Conversely, using the 2018 holiday model as base year model to predict 2019 holiday crashes overestimated severe and fatal injuries and underestimated minor injury crashes

The findings from these series of out-of-sample prediction simulations clearly illustrated the expected temporal instability and differences between the effects of weekday, weekend, and holiday crashes on motorcyclist injury severity distribution. The differences between time-of-year crashes on resulting motorcyclist injury severity may be attributed to factors such as trip purposes, traffic volumes, traffic compositions, human attitudes/behaviors/activities/cultures and policy implementations (for example, law enforcement on drunk driving is more strictly implemented during weekends and holidays, and more medical services are offered outside the hospital during holiday periods) which vary by time-of-year. Regarding temporal shift, weekday motorcycle crashes constantly worsened over the studied periods (2016-2019), whereas a slight improvement was observed in 2019 weekend and holiday motorcycle crashes. While the exact reasons are unclear, these changes could be attributed to varying in riding experiences, new technologies and other advancements introduced to motorcycles, macroeconomic conditions, and changes of rider attitudes and behaviors as a response to the changes of other road users (including cars, buses, vans, trucks, etc.) due to the evolution of vehicle technologies, other social media platforms and various safety education campaigns (Alnawmasi and Mannering, 2019; Mannering, 2018).

It is noteworthy that the nontransferability found in this study may also partially uncover the effect of self-selectivity (see Mannering (2018) and Mannering et al. (2020) for detailed discussion of the issues related to self-selectivity bias in crash severity research). Although it is not possible to untangle the true effects of behaviors and self-selectivity with the current data, the behavioral differences may partially play role in the causes of the observed instability between time-of-year models (e.g., behavior of a particular rider may potentially shift or change from weekday to weekend and to holiday depending on the trip purpose). Additionally, it could also be due to the fact that different people tend to ride motorcycle on weekend, weekday, and holiday. This instability possibly captures the effect of the self-selective nature of the motorcyclist who chooses to ride on different time-of-year. For example, weekday motorcyclists may include more number of student and local-stakeholder riders, whereas weekend motorcyclists may include more number of riders traveling to/from entertainment or shopping centers (particularly during nighttime), whereas holiday motorcyclists may include more number of long-distance travelers (e.g., visiting relatives/family at hometown etc.), drunk riders, riders who ride on unfamiliar roadway environments, riders who choose to travel under well-informed interest in a particular situation (for example, in the case of Thai Songkran festival, riders are aware of riding on wet road surfaces and being splashed with water, etc.).

4.9 Summary and Conclusions

Crashes involving motorcycles remain a major concern for road users and highway administrators, as they constitute the highest fatality rates compared with crashes that do not involve motorcycles (which are much more serious in developing countries than in developed countries). The current study took a different perspective from those of other motorcycle crash injury severity studies by examining the differences between the effects of weekday, weekend, and holiday crashes on motorcyclist injury severity using motorcycle crash data in Thailand from 2016 to 2019 while also accounting for the temporal shift. To account for unobserved heterogeneity, the latest methodological approaches (a random parameters logit model with heterogeneity in means and variances) were utilized using three injury severity levels (minor, severe, and fatal). The extensive series of likelihood ratio tests clearly indicated that the model estimates between weekday, weekend, and holiday crashes were nontransferable in all years, and substantial temporal instability from 2016 to 2019 was present in all time-of-year model specifications. In addition, many statistically significant factors were found to have influence on motorcyclist injury severity probabilities in various time-of-year and yearly models.

Although the majority of the variables showed opposite effects between weekday, weekend, and holiday crashes, other variables generated the same effect on resulting motorcyclist injury probabilities (including variables that increase the likelihood of severe and fatal injuries, such as riding with a pillion, four lanes, two lanes, curves, grades, intersections, lit roads, unlit roads, midnight/early morning, hitting pickup/van/bus/truck, and head-on crashes; and variables that increase the likelihood of minor injury, such as hitting motorcycles and urban areas).

With regard to the temporal stability assessment, four variables were stable across all periods in the weekday model (hitting-motorcycle and urban indicators increasing the likelihood of minor injury and hitting-truck and midnight/early morning indicators increasing the likelihood of fatal injury). For weekend crashes, variables showed temporal stability across all periods, including four-lane roads, two-lane roads, hitting motorcycles, and hitting trucks (only the hitting-motorcycle indicator increased the likelihood of minor injury, while all others increased the likelihood of fatal injury). Only two variables had stable effects in the holiday model, including riding with a pillion and hitting passenger cars, with the effects increasing the likelihood of fatal injury. Also worth noting is that many variables were also found significant in only three year models with temporal stability, which can also serve as a key finding for policy formation. For example, unlit roads, midnight/early morning, evening, hitting vans, hitting trucks, and head-on crashes were significant in three time periods in the holiday models with effects increasing the likelihood of fatal injury.

The results of the prediction comparison clearly illustrated substantial differences between weekday, weekend, and holiday motorcyclist injury severity probabilities. For example, using weekday model estimates to predict actual weekend crash characteristics would expect more minor injuries in all four periods but fewer fatal injuries from 2016 to 2019; while severe injury probability was overestimated in some periods. However, using weekday or weekend model estimates to predict actual holiday crash characteristics would underestimate minor and severe injuries and overestimate fatal injury in all four yearly models. Overall, most fatal injuries are expected from motorcycle crashes during weekends followed by those during weekdays whereas most severe injuries would be expected during holidays. In addition, the prediction simulation for temporal stability in each time-of-year model result clearly showed evidence of temporal instability throughout all the examined years (using the prior-year model estimate to predict later-year crash characteristics, the weekday model stably overestimated minor injuries in all subsequent years and underestimated severe and fatal injuries, whereas weekend and holiday models showed variations in prediction).

Overall, this paper highlights the importance of accounting for time-of-year transferability and temporal instability with unobserved effects in determinants affecting motorcyclist injury severity. With diverging results between weekdays, weekends, and holidays, the present findings offer new insights that could serve as guidelines for practitioners, researchers, institutions, and decision-makers to enhance highway safety, especially motorcyclist safety, and facilitate the development of more effective policies that prevent motorcycle crash injuries.

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CHAPTER V

DAY AND NIGHT VARIATION OF FACTORS IMPACTING MOTORCYCLIST INJURY SEVERITIES: ACCOUNTING FOR POTENTIAL TEMPORAL SHIFTS AND UNOBSERVED EFFECTS

5.1 Abstract

Given the fact that the motorcycle-involved crashes remain a serious global issue and are associated with a disproportionate number of fatalities and severe injuries, this paper investigates the differences between daytime and nighttime resulting motorcyclist-injury severities, and how these differences changed over time, using four years of crash data in Thailand from 2016 to 2019. To systematically account for unobserved heterogeneity in the data, mixed ordered probit model with possible heterogeneity in means and variances of random parameters were estimated considering three possible injury-severity outcomes (minor injury, severe injury, and fatal injury). Wide varieties of variables were considered in model estimation including motorcyclist characteristics, roadways characteristic, environmental characteristics, and crash characteristics. Both likelihood ratio tests and model estimation results confirm that there were significant differences in daytime and nighttime motorcyclist injury severity, and that the effect of the determinants are statistically unstable over time. It is noteworthy that some variables had a strikingly high probability of fatal injury include overtaking illegally, fatigue riders, 2 lanes, bridge location, wet road surface, hitting a truck and head-on crash. In most of the cases, nighttime crashes consistently result in a more severe injuries (and higher probability). The findings of this paper could provide new insights into motorcycle safety, which can be of value to decision/policy makers, traffic management departments and roadway designers seeking to promote highway safety targeted motorcycle road users.

5.2 Introduction

Undoubtedly, Road Traffic Crashes (RTC) remain a major public health burden causing huge numbers of avoidable deaths and disabilities, with over 1.3 million people killed and up to 50 million injured globally every year (WHO, 2017). Inevitably, Road Traffic Injuries (RTI) has serious consequences including extra burden on health systems and countries, loss of human resources, and untold or unseen misery and economic consequences to families who have to deal with bereavement or disabled relative (Bryant et al., 2004; Masilkova, 2017; Mayou and Bryant, 2003; Mitchell, 1997; WHO, 2017). Among these deaths and injuries, nearly 90% occur in low- and middle-income countries. Particularly in the Southeast Asia region, the death rate due to RTC is approximately 316, 000 victims per year, and the so-called vulnerable road users such as pedestrians, cyclists and motorcyclists make up 50% of deaths on the road in the Region (WHO, 2017). In Thailand as part of Southeast Asia region, RTC that involving motorcycle users are on average of 3,883 cases per year which is approximately 30% of non-motorcycle-related crash types combined (see **Figure 5.1**; based on 2016 to 2019 crash record statistic from the Department of Highway (DOH), Thailand). In addition, looking at deaths by road user category based on a World Health Organization report in 2016, motorcycle riders accounted for approximately over 70% of the total deaths due to RTI on Thailand roadways—the highest compared to other road users (see **Figure 5.2**). In 2018, although Thailand's rank has dropped from second to ninth on the world's list of most dangerous roads; yet, one thing remains the same—road traffic deaths among motorcyclists in Thailand are still the highest in the world (WHO, 2018). The safety of motorcycle riders must be addressed vigorously if a reduction in the number of deaths is to be achieved. These situations entail an in-depth research concerning the occurrences and resulting injury severities of crashes involving motorcycle users, which requires further investigation to provide insightful knowledge for developing appropriate and targeted strategies for crash mitigation and prevention

With respect to the time-of-day, Behnood and Mannering (2019) points out two sources that may explain the variability of effect of the contributing factors on resulting injury severity: 1) human behavior (decision making, response, alertness, etc.) may varies throughout the day (due to fatigue, bio-rhythm, sleep deprivation etc.) and unobserved factors related to visibility, lighting, and so on may potentially vary by time-of-day. Taking this into consideration, numerous crash severity studies have extensively considered the effect of time-of-day on the resulting injury severities. Those studies include driver's injury severity at highway-rail grade crossing (Hao et al., 2016), pedestrian-involved crashes (Mokhtarimousavi, 2019), large-truck crashes severity (Behnood and Mannering, 2019), pedestrian-injury severities (Alogaili and Mannering, 2022; Song et al., 2021b), injury severity of crashes on mountainous expressway in China (Peng et al., 2021), crash severity of work zone crashes (Zhang and Hassan, 2019), and bicycle-vehicle crashes severity (Liu et al., 2021). These studies suggest that time-of-day may have a significant role in resulting crash injury severities, and that this role may go beyond the simple use of indicator variables (indicating various time of day intervals) in statistical models (Behnood and Mannering, 2019). That being said, this paper intends to consider the possibility that the effect of all factors that determine injury severities may vary by time of day (specifically daytime and nighttime) as opposed to a simple shift in probabilities that results with the use of explanatory variables.

Another important aspect when investigating the factors associated with crash injury severities, there is a growing body of empirical evidence that rejects the null hypothesis that the effects of injury-severities contributing factors are temporally stable over time (Behnood and Mannering, 2019). Based on a detail reviews on the necessity to account for temporal instability by F. Mannering (2018), it is strongly recommended to consider the temporal elements associated with individual behavior and the aggregate trends when developing modeling approaches and interpreting model findings; and ignoring these fundamental temporal elements can lead to erroneous conclusions and ineffective or even dangerous safety policies. In this regard, numerous researcher have recently taken effort to fully account for temporal influence in their crash severity study (Alnawmasi and Mannering, 2022; Alogaili and Mannering, 2022; Fanyu et al., 2021; Hou et al., 2021; M. Islam and Mannering, 2021; Y. Li et al., 2021; Se et al., 2021b; Song et al., 2021a; Yan et al., 2021a; Yan et al., 2022; Yan et al., 2021b; Yu et al., 2021; Zamani et al., 2021). In addition to investigating temporal instability, these studies also utilized the methodological approaches that have the capabilities to account for potential heterogeneity which is also necessary in crash injury-severities analysis to capture unobserved effect underlying crash data (F. L. Mannering et al., 2016).

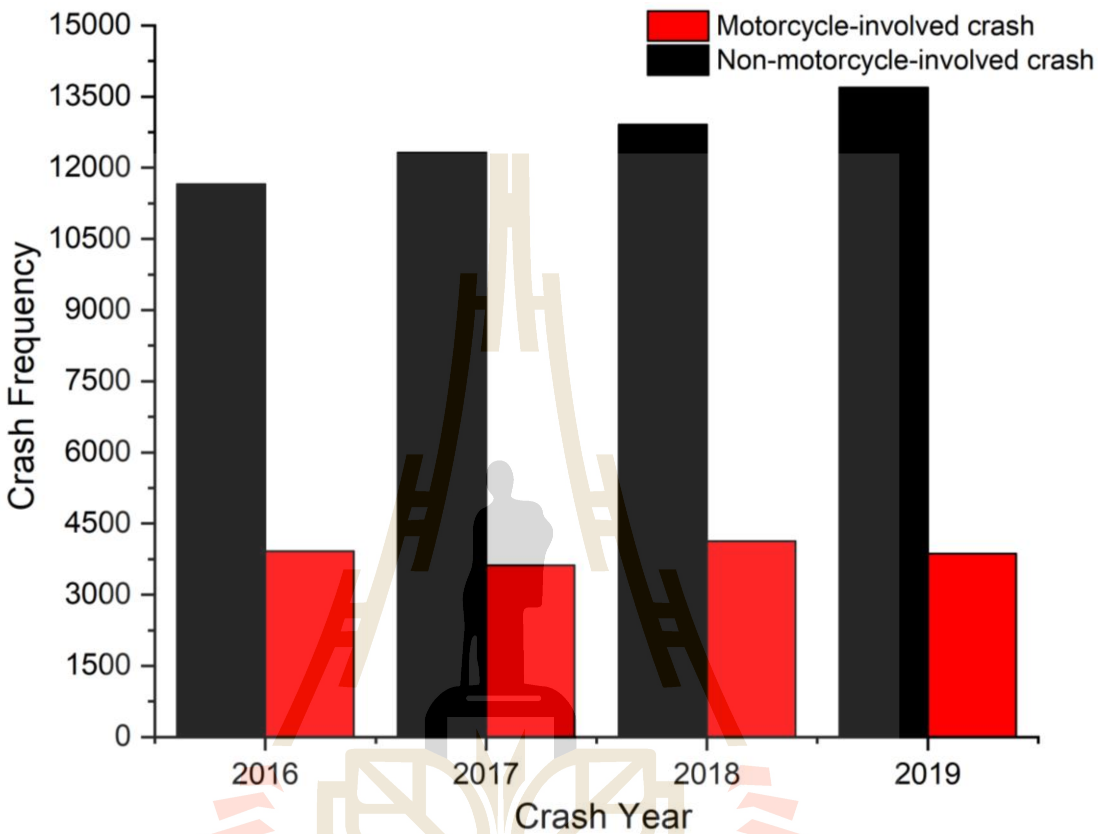


Figure 5.1 A comparison of crash frequency between motorcycle-involved crashes versus non-motorcycle-involved crashes in Thailand from 2016—2019, based on crash data of Department of Highways (DOH)

With the above-mentioned issues in mind, the objective of this study is particularly interested in in-depth understanding of the following problems:

a) What are the contributing factors to motorcyclist injury severities of crashes on highways?

b) What contributing factors have heterogeneous effects on resulting motorcyclist injury severities?

c) What are the differences in the impact degree of factors between the daytime and nighttime motorcycle crashes?

d) Are the effects of risk factors impacting motorcyclist injury severities of the daytime and nighttime motorcycle crashes temporally stable?

The remainder of the paper is organized as follows. **Section 5.3** reviews the factors affecting motorcycle crash injury severities and methodological approaches for motorcycle crash severity modelling. **Section 5.4** presents the description of the available crash data; **Section 5.5** presents the development of a methodological framework. **Section 5.6** discusses the likelihood ratio test for transferability (between daytime and nighttime crash) and temporal stability (yearly). **Section 5.7**: presents the discussion of the model estimation result, and **Section 5.8**: summarizes the findings, conclusion and proposing the policy-related recommendations for motorcyclist injury severity mitigations.

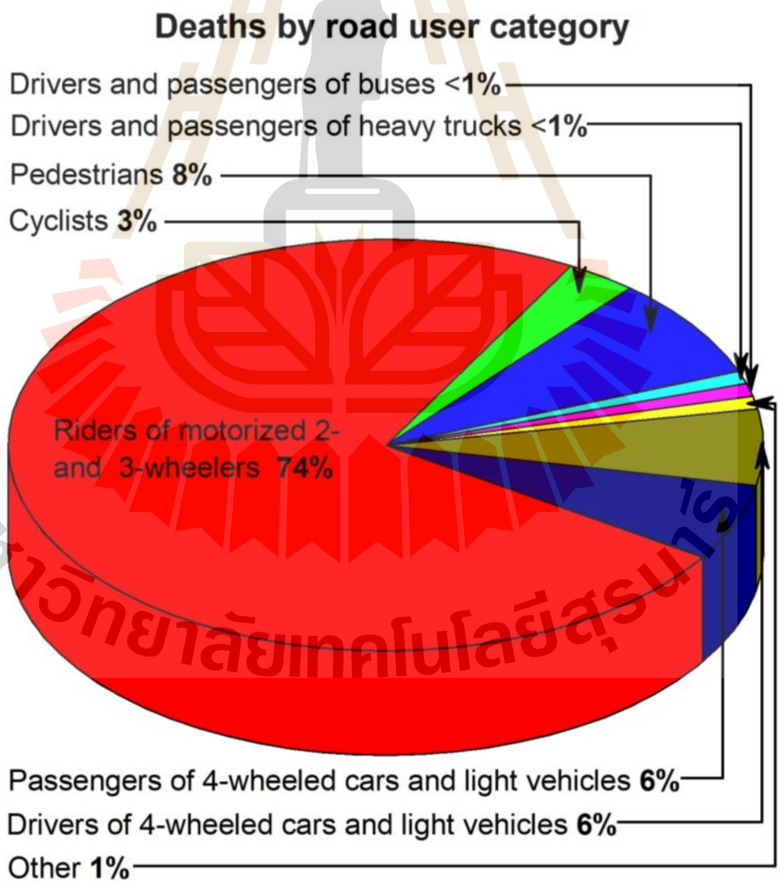


Figure 5.2 2016, Injury surveillance system, Bureau of Epidemiology, Department of Disease Control, Ministry of Public Health (*Source: adapted from Global status report on road safety 2018* [WHO, 2018])

5.3 Literature Review

5.3.1 Review of previous motorcycle crash severity studies' general finding

Previous studies have identified numerous variables as contributors determining different levels of motorcycle crash injury severities that can be categorized into rider characteristics, motorcycle characteristics, roadway characteristics, crash characteristics, environmental characteristics, and temporal characteristics. A summary of key findings of the past literatures are provided below.

Rider characteristics/actions: regarding age of rider, increasing in age are positively associated with incapacitating- and fatal injury (Cunto and Ferreira, 2017; Pai, 2009; Savolainen and Mannering, 2007; Schneider and Savolainen, 2011), riders older than 50 years of age are also positively associated with severe and fatal injury (Geedipally et al., 2011; Xin et al., 2017), whereas young riders (25 or less year old) are positively associated with no injury and minor injury (Geedipally et al., 2011; M. S. Shaheed and Gkritza, 2014; Wang et al., 2014). In terms of rider's gender, compared to female riders, while some studies (Pai and Saleh, 2008; M. S. Shaheed and Gkritza, 2014; Wang et al., 2014) found that male riders are positively associated with incapacitating and fatal injury, other studies (Geedipally et al., 2011; Jung et al., 2013; M. S. B. Shaheed et al., 2013; Xin et al., 2017) found that male rider have lower likelihoods of fatality and incapacitating injury. While there is a clear conflict in effect of gender on rider injury severities, Se et al. (2022b) found that specific gender (either male or female) has heterogenous effect on resulting injury severity (i.e., a cohort increasing the injury level and leftover cohort decreasing injury level). In terms of rider conditions, impaired riders and riders under influence of alcohol are positively associated with minor and severe injury in motorcycle crashes (Albalate and Fernández-Villadangos, 2010; Alnawmasi and Mannering, 2019; Geedipally et al., 2011; X. Li et al., 2021; Rifaat et al., 2012; Savolainen and Mannering, 2007; Schneider and Savolainen, 2011; Zambon and Hasselberg, 2006). In addition, riders using unsafe speed or exceeding posted speed-limit are positively associated with increasing level of injury severity (Alnawmasi and Mannering, 2019; Chang et al., 2021; Rifaat et al., 2012; Savolainen and Mannering, 2007; M. S. Shaheed and Gkritza, 2014; M. S. B. Shaheed et al., 2013; Waseem et al., 2019; Zambon and Hasselberg, 2006); whereas riders wearing helmet are negatively associated with severe and fatal injury in motorcycle-involved crashes (Alnawmasi and Mannering, 2019; Chang et al., 2016; S. Islam and Brown, 2017; Kashani et al., 2014; X. Li et al., 2021; Xin et al., 2017). In terms of rider's actions, improper riding such as weaving through traffic and illegal overtaking are positively associated with severe and fatal injury (Chung et al., 2014; Se et al., 2021a; Se et al., 2022b). Lastly, presence of pillion also results in conflict finding among existing literatures: some studies (Ijaz et al., 2021; Kashani et al., 2014; Savolainen and Mannering, 2007; Se et al., 2021a) found that riding with pillion is positively associated with higher injury severity level, whereas other studies (X. Li et al., 2021; Schneider and Savolainen, 2011) reported that presence of pillion is negatively associated with severe and fatal injury.

Motorcycle characteristics: Regarding engine of motorcycle, increase in motorcycle engine sizes are positively associated with a higher probability of severe and fatal injury in motorcycle crashes (De Lapparent, 2006; Pai, 2009; Waseem et al., 2019). In addition, riders using sport bikes are positively associated with non-incapacitating injury in the crashes (Savolainen and Mannering, 2007).

Roadways characteristics: Regarding roadway alignments, motorcycle crashes on horizontal curves are positively associated with an increase in injury-severity level (Chang et al., 2016; Geedipally et al., 2011; M. Islam, 2021; X. Li et al., 2021; Wang et al., 2014), and motorcycle crash on graded road are also positively associated with higher injury severity levels (Alnawmasi and Mannering, 2019; Chang et al., 2016; Se et al., 2021a; Se et al., 2022b). Motorcycle crashes occurred on the auxiliary or frontage lane are negatively associated with fatality and severe injury crash (Se et al., 2021a; Xin et al., 2017). Regarding crash at intersection area, previous studies (Chang et al., 2016; Geedipally et al., 2011; S. Islam and Brown, 2017; Savolainen and Mannering, 2007) found that riders experience a lower probability of severe and fatal injury; whereas some recent studies (Tamakloe et al., 2022; Vajari et al., 2020) found that motorcycle crash at intersection are positively associated with higher injury severity level. While there is a certain conflict finding among previous works for motorcycle crash, other studies found that riders injury severities significantly vary across crash observation which may be due to unknown characteristic or effect (Se et al., 2021a;

Se et al., 2022b). In terms of region, compared to urban road, motorcycle crashes on rural road are positively associated with incapacitating injury and fatality (Kashani et al., 2014; X. Li et al., 2021; M. S. Shaheed and Gkritza, 2014; Vajari et al., 2020; Zambon and Hasselberg, 2006). Interestingly, regarding pavement surface condition, previous studies found that motorcycle crashes on good pavement surface condition have higher probability of injury and fatal crashes (Geedipally et al., 2011), whereas crashes poor pavement condition are negatively associated with severe and fatal injury (Xin et al., 2017). In terms of posted speed limit, riders have higher probability of severe injury in a crash on road with higher posted speed limit (M. S. Shaheed and Gkritza, 2014; M. S. B. Shaheed et al., 2013; Waseem et al., 2019; Zambon and Hasselberg, 2006). Conflict finding also found regarding motorcycle crashes at U-turn area, some studies found it increase the likelihoods of severe and fatal injury crash (Se et al., 2021a; Se et al., 2022b), whereas other studies found such crashes are negatively associated with higher injury severity (Ijaz et al., 2021; Sivasankaran et al., 2021).

Environmental and temporal characteristics: Regarding road surface conditions, interestingly, past studies (Jung et al., 2013; Savolainen and Mannering, 2007) reported that motorcycle crashes on wet road surface are negatively associated with severe and fatal injury and crashes under adverse weather (rain, fog snow, etc.) are positively associated with no and minor injury (Schneider and Savolainen, 2011; Se et al., 2022b); whereas crashes on dry road condition have higher probability of severe and fatal injury (M. S. Shaheed and Gkritza, 2014; M. S. B. Shaheed et al., 2013). In terms of lighting conditions, previous research (Chang et al., 2016; Cunto and Ferreira, 2017; Schneider and Savolainen, 2011; Se et al., 2022b; M. S. B. Shaheed et al., 2013; Wang et al., 2014) reported that daylight crashes have lower probability of severe and fatal injury, compared to nighttime motorcycle crashes. Regarding time-of-day, motorcycle crashes during midnight to early morning hours have higher probability of severe and fatal injury (Pai, 2009; Quddus et al., 2002; Se et al., 2021a). Similarly, previous works (Cunto and Ferreira, 2017; Jung et al., 2013; Se et al., 2022b; M. S. Shaheed and Gkritza, 2014) reported that motorcycle crashes on weekends are positively associated with more severe injury.

Crash characteristics: Previous studies found that riders hitting a fixed

-object have a higher probability of incapacitating and fatal injury (Savolainen and Mannering, 2007; Schneider and Savolainen, 2011; M. S. Shaheed and Gkritza, 2014; Shankar and Mannering, 1996; Waseem et al., 2019; Xin et al., 2017). Similarly, motorcycle run-off-road and rollover crashes (Savolainen and Mannering, 2007; M. S. Shaheed and Gkritza, 2014), and hitting a heavy vehicle or automobile with large engine size (De Lapparent, 2006; Rifaat et al., 2012; Waseem et al., 2019) are associated with higher injury severity in motorcycle crashes. Single-motorcycle crashes, angular crashes and head-on crashes are positively associated with higher injury severity level (Chang et al., 2021; Geedipally et al., 2011; Jung et al., 2013; X. Li et al., 2021; Schneider and Savolainen, 2011; Zambon and Hasselberg, 2006).

In summary, it is noteworthy that although there are several broad agreements among findings regarding factors affecting motorcycle crash injury severity, there are also some conflicting findings among existing literature. In addition, though some factors had the same influence on injury across different studies, the magnitudes of the effects observably vary. This may be attributed to the use of different methodological approaches, different sample sizes (those with low observation of accident data could suffer from omitted-variable bias), different locations of data collection, and, more importantly, different periods of data collection (Alnawmasi and Mannering, 2019; F. Mannering, 2018; F. L. Mannering et al., 2016). These reasons could also potentially differentiate the current study from previous research.

5.3.2 Review of motorcycle crash severity modeling methodologies

Table 5.1 provides the methodological approaches utilized in the previous studies to analyze injury severity in motorcycle crashes. These approaches are categorized into three group: ordered response, unordered response and data-driven approaches (Yan et al., 2022). Selection of approach for analysis often come to an implicit trad-off between big-data suitability, predictive capability of the resulting analysis (data-driven approach generally offers this capability better than econometric approaches) and inference capability (i.e., ability to uncover the underlying effect and causality of crash-contributing factors; econometric approaches generally offer this capability better than data driven approach) (F. Mannering et al., 2020). As presented in **Table 5.1**, some of the advance heterogeneity models (F. L. Mannering et al., 2016)

Table 5.1 Methodological approaches utilized in the previous motorcyclist injury-severities research

Methodological approach	Previous research
Ordered response models	
Ordered logit model	Albalate and Fernández-Villadangos (2010); Rifaat et al. (2012); Sivasankaran et al. (2021)
Ordered probit model	Quddus et al. (2002); Chung et al. (2014)
Generalized ordered logit model	Rifaat et al. (2012)
Geographically-Temporally Weighted Ordered Logistic Regression	X. Li et al. (2021)
Mixed ordered logit model	Chang et al. (2016); Cunto and Ferreira (2017)
Correlated random parameters ordered probit with heterogeneity in means model	Se et al. (2021)
Latent class ordered probit model	J. Li et al. (2021)
Latent class clustering and latent segmentation-based based on ordered logit models	Chang et al. (2021)
Unordered response models	
Binary logit model	Pai (2009); Rahman et al. (2021)
Univariate and multivariate stepwise logistic regression model	Zambon and Hasselberg (2006)
Empirical Bayesian method based on the Multinomial-Dirichlet model	De Lapparent (2006)
Nested logit model	Savolainen and Mannering (2007)
Multinomial logit model	Savolainen and Mannering (2007); Schneider and Savolainen (2011); Geedipally et al. (2011);

Table 5.1 Methodological approaches utilized in the previous motorcyclist injury-severities research (Cont.)

Methodological approach	Previous research
Mixed-effect logit model	Xin et al. (2017)
Random parameters logit model	M. S. B. Shaheed et al. (2013); S. Islam and Brown (2017)
Random parameters binary probit with heterogeneity in means and variance model	Se et al. (2022)
Random parameters logit with heterogeneity in means and variance model	Waseem et al. (2019); Alnawmasi and Mannering (2019); Ijaz et al. (2021); M. Islam (2021)
Latent class multinomial logit model	M. S. Shaheed and Gkritza (2014)
Data-driven approaches	
Classification and Regression Trees (CART) model	Kashani et al. (2014); Rezapour et al. (2020a)
Artificial Neural Networks (ANN) model	Se et al. (2022)
Deep learning techniques	Rezapour et al. (2020b)

employed in motorcycle crash injury severity studies include mixed ordered logit model (Chang et al., 2016; Cunto and Ferreira, 2017), correlated random parameters ordered probit with means heterogeneity model (Se et al., 2021a), latent class ordered probit model (J. Li et al., 2021), latent class clustering and latent segmentation-based based on ordered logit models (Chang et al., 2021), mixed logit model (S. Islam and Brown, 2017; M. S. B. Shaheed et al., 2013), random parameters logit/probit with means and variance heterogeneity model (Alnawmasi and Mannering, 2019; Ijaz et al., 2021; M. Islam, 2021; Se et al., 2022b; Waseem et al., 2019), and latent class multinomial logit model (M. S. Shaheed and Gkritza, 2014). The selection process between uncorrelated model (particularly, variances heterogeneity) and correlated model (allowing interaction among random parameters) should depend on the practical application of the research objective by considering the best trade-off between model fit, prediction accuracy, and explanatory power in determining the best model specification (Ahmed et al., 2021; Se et al., 2021b). In addition, choosing between the unordered and ordered response heterogeneity models could be a tedious task since both approaches share benefits and limitations (Fountas and Anastasopoulos, 2017). However, owing to the ordered nature of crash injury severity level, some studies argue that crash-injury severity research require framework with ability to account for natural order of the severity level (e.g., from no injury to minor injury to severe injury and to fatal injury) and unobserved heterogeneity inherent in the effect of crash-level factor and severity level (Song and Fan, 2020). Therefore, in this study, a mixed ordered probit model accommodating possible heterogeneity in means and variances of random parameters was adopted (which is an extension of the methodological approach of the previous motorcycle crash analysis studies (Chang et al., 2016; Cunto and Ferreira, 2017) by allowing the model to capture underlying unobserved heterogeneity in a more flexible way).

5.4 Data Description

The data on reported motorcycle crashes were collected for the 4 years period from 2016 to 2019 from the crash database maintained by Thailand Department of Highways (DOH). The report covered the traffic crash data that occurred nationwide on Thai highways. All crash records were surveyed and uploaded into Highways Accident Information Management System database (HAIMS) of the DOH, by the police officers. Crash data was then gone through a data screening and cleaning process. In total, 13795 of motorcycle crash cases with complete detailed information were filtered for the data analysis, which were then separated into yearly daytime and nighttime data. Finally, daytime data contained 38 attributes; whereas nighttime data contained 39 attributes (additional factor is “unlit road”). These attributes were categorized into four groups including rider characteristic, roadway characteristics, environmental characteristic, and crash characteristics. Three levels of motorcyclist injury severities were considered in this study: minor injury (little to no injury or properties damage only [PDO]), severe injury [fully recovered from the injuries sustained after three weeks or more, and fatal injury (died at the crash scene or at the hospital). As illustrated in

Figure 5.3, while proportions of severe injury crash of daytime and nighttime are approximately equal (20% relative to their respective total number of crash), the fatal injury proportion of nighttime crash was remarkably higher than that of daytime crash (40.21% in nighttime compared to 26.42 in daytime). This, in general, clearly indicated that riders involved in nighttime crashes had a higher possibility of being killed in the crash compared to daytime. In addition, the shift in proportion and frequency of each motorcyclist injury severity from one year to the next were also observed. **Table 5.2** shows the summary descriptive statistics of the explanatory variables by time-of-day and year in Thailand between 2016 to 2019.

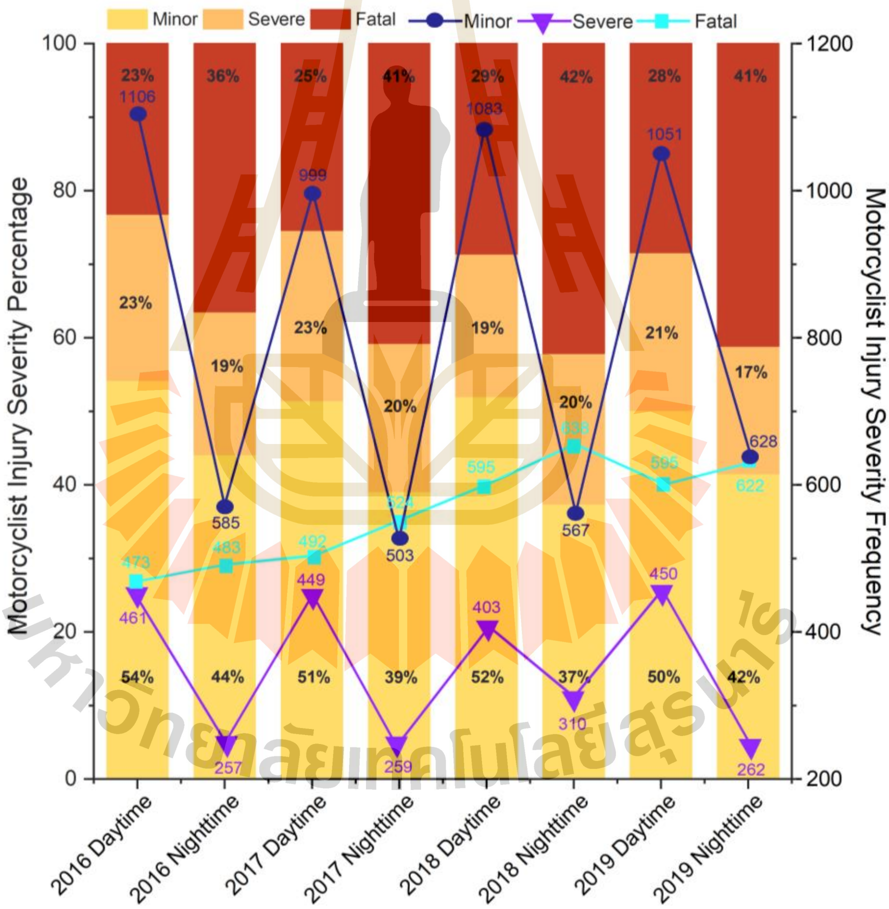


Figure 5.3 Daytime and nighttime motorcyclist injury severity distribution and frequency in Thailand over the years: 2016–2019

Table 5.2 Descriptive statistics of the explanatory variables

Explanatory variable	2016				2017				2018				2019			
	Daytime		Nighttime		Daytime		Nighttime		Daytime		Nighttime		Daytime		Nighttime	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Rider characteristics																
Gender (1 if male, 0 female)	0.761	0.427	0.851	0.356	0.739	0.439	0.869	0.338	0.740	0.439	0.855	0.352	0.745	0.436	0.849	0.358
Pillion (1 if yes, 0 otherwise)	0.340	0.474	0.313	0.464	0.325	0.468	0.305	0.461	0.329	0.470	0.314	0.464	0.329	0.470	0.326	0.469
Exceeding speed limit (1 if yes, 0 otherwise)	0.638	0.481	0.702	0.458	0.568	0.495	0.676	0.468	0.593	0.491	0.651	0.477	0.565	0.496	0.679	0.467
Hit a crossing object (1 if yes, 0 otherwise)	0.264	0.441	0.141	0.348	0.297	0.457	0.160	0.367	0.291	0.454	0.170	0.376	0.313	0.464	0.158	0.365
Illegal overtaking (1 if yes, 0 otherwise)	0.017	0.128	0.011	0.102	0.016	0.127	0.014	0.118	0.013	0.113	0.013	0.111	0.010	0.100	0.007	0.081
Alcohol (1 if yes, 0 otherwise)	0.027	0.162	0.075	0.263	0.039	0.193	0.081	0.273	0.033	0.179	0.084	0.278	0.029	0.167	0.079	0.270
Fatigue (1 if yes, 0 otherwise)	0.006	0.076	0.006	0.077	0.013	0.113	0.009	0.092	0.011	0.102	0.009	0.096	0.012	0.111	0.011	0.102
Roadway characteristics																
Main lane (1 if yes, 0 otherwise)	0.046	0.209	0.053	0.224	0.055	0.228	0.067	0.250	0.070	0.255	0.063	0.244	0.023	0.150	0.031	0.174
Frontage lane (1 if yes, 0 otherwise)	0.057	0.233	0.057	0.231	0.059	0.236	0.058	0.234	0.042	0.200	0.044	0.206	0.040	0.195	0.042	0.200
Work zone (1 if yes, 0 otherwise)	0.025	0.158	0.035	0.183	0.021	0.142	0.018	0.133	0.015	0.121	0.020	0.142	0.015	0.121	0.026	0.161
2 Lanes (1 if yes, 0 otherwise)	0.347	0.476	0.330	0.470	0.352	0.478	0.312	0.463	0.369	0.483	0.338	0.473	0.344	0.475	0.340	0.474
4 Lanes (1 if yes, 0 otherwise)	0.404	0.491	0.387	0.487	0.424	0.494	0.416	0.493	0.391	0.488	0.404	0.491	0.442	0.497	0.413	0.493
Flush median (1 if yes, 0 otherwise)	0.082	0.274	0.057	0.231	0.105	0.307	0.096	0.295	0.112	0.316	0.119	0.324	0.135	0.342	0.115	0.319

Table 5.2 Descriptive statistics of the explanatory variables (Cont.)

Explanatory variable	2016				2017				2018				2019			
	Daytime		Nighttime		Daytime		Nighttime		Daytime		Nighttime		Daytime		Nighttime	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Raised median (1 if yes, 0 otherwise)	0.206	0.404	0.239	0.427	0.210	0.407	0.222	0.415	0.262	0.440	0.283	0.450	0.244	0.429	0.249	0.432
Depressed median (1 if yes, 0 otherwise)	0.160	0.367	0.162	0.368	0.164	0.371	0.174	0.379	0.174	0.379	0.171	0.377	0.198	0.399	0.208	0.406
Barrier median (1 if yes, 0 otherwise)	0.116	0.320	0.123	0.329	0.093	0.291	0.124	0.330	0.069	0.253	0.082	0.274	0.064	0.245	0.075	0.263
Concrete road (1 if yes, 0 otherwise)	0.106	0.308	0.124	0.329	0.090	0.286	0.111	0.314	0.132	0.338	0.129	0.335	0.126	0.332	0.134	0.340
Curve (1 if yes, 0 otherwise)	0.097	0.296	0.100	0.301	0.115	0.320	0.114	0.318	0.134	0.340	0.094	0.292	0.115	0.318	0.102	0.303
Grade (1 if yes, 0 otherwise)	0.030	0.170	0.026	0.160	0.033	0.179	0.028	0.165	0.033	0.179	0.024	0.154	0.030	0.171	0.025	0.157
4-leg intersection (1 if yes, 0 otherwise)	0.046	0.209	0.041	0.198	0.046	0.210	0.030	0.172	0.047	0.211	0.040	0.195	0.050	0.218	0.035	0.184
3-leg intersection (1 if yes, 0 otherwise)	0.087	0.282	0.056	0.230	0.087	0.281	0.054	0.225	0.079	0.270	0.058	0.234	0.057	0.232	0.048	0.214
U-turn (1 if yes, 0 otherwise)	0.077	0.267	0.072	0.258	0.101	0.301	0.075	0.263	0.085	0.279	0.055	0.229	0.065	0.247	0.035	0.184
Bridge (1 if yes, 0 otherwise)	0.011	0.106	0.017	0.128	0.010	0.099	0.008	0.088	0.011	0.105	0.011	0.102	0.009	0.092	0.013	0.111
Urban road (1 if yes, 0 otherwise)	0.227	0.419	0.252	0.434	0.180	0.384	0.216	0.412	0.202	0.401	0.192	0.394	0.186	0.389	0.194	0.396
Environmental characteristics																
Wet road (1 if yes, 0 otherwise)	0.031	0.173	0.036	0.187	0.057	0.232	0.082	0.275	0.042	0.200	0.065	0.246	0.031	0.172	0.047	0.212
Raining (1 if yes, 0 otherwise)	0.025	0.156	0.048	0.213	0.057	0.232	0.103	0.305	0.038	0.191	0.067	0.250	0.029	0.168	0.075	0.263
Holiday (1 if yes, 0 otherwise)	0.446	0.497	0.455	0.498	0.443	0.497	0.482	0.500	0.454	0.498	0.510	0.500	0.406	0.491	0.462	0.499

Table 5.2 Descriptive statistics of the explanatory variables (Cont.)

Explanatory variable	2016				2017				2018				2019			
	Daytime		Nighttime		Daytime		Nighttime		Daytime		Nighttime		Daytime		Nighttime	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Weekend (1 if yes, 0 otherwise)	0.301	0.459	0.297	0.457	0.296	0.457	0.325	0.469	0.258	0.437	0.306	0.461	0.288	0.453	0.332	0.471
Unlit (1 if yes, 0 otherwise)	-	-	0.285	0.451	-	-	0.288	0.453	-	-	0.276	0.447	-	-	0.282	0.450
Crash characteristics																
Hit a motorcycle (1 if yes, 0 otherwise)	0.142	0.349	0.097	0.296	0.119	0.323	0.111	0.314	0.127	0.333	0.094	0.292	0.110	0.313	0.105	0.307
Hit a passenger car (1 if yes, 0 otherwise)	0.309	0.462	0.257	0.437	0.273	0.445	0.236	0.425	0.292	0.455	0.217	0.412	0.260	0.438	0.215	0.411
Hit a pickup truck (1 if yes, 0 otherwise)	0.282	0.450	0.207	0.405	0.299	0.458	0.196	0.397	0.307	0.461	0.217	0.412	0.350	0.477	0.247	0.431
Hit a van/minibus (1 if yes, 0 otherwise)	0.051	0.220	0.052	0.222	0.057	0.231	0.049	0.216	0.048	0.213	0.041	0.198	0.031	0.173	0.029	0.168
Hit a truck (1 if yes, 0 otherwise)	0.080	0.272	0.103	0.304	0.087	0.281	0.117	0.321	0.086	0.280	0.109	0.312	0.092	0.289	0.106	0.309
Rear-end crash (1 if yes, 0 otherwise)	0.353	0.478	0.316	0.465	0.354	0.478	0.333	0.471	0.370	0.483	0.318	0.466	0.378	0.485	0.349	0.477
Sideswipe crash (1 if yes, 0 otherwise)	0.247	0.431	0.177	0.381	0.239	0.427	0.170	0.376	0.298	0.458	0.207	0.405	0.280	0.449	0.200	0.400
Single-motorcycle crash (1 if yes, 0 otherwise)	0.159	0.366	0.248	0.432	0.183	0.387	0.257	0.437	0.165	0.372	0.296	0.457	0.173	0.378	0.295	0.456
Head on crash (1 if yes, 0 otherwise)	0.049	0.215	0.042	0.200	0.054	0.226	0.051	0.219	0.102	0.303	0.085	0.279	0.086	0.280	0.080	0.271

5.5 Methodology

To capture the heterogeneous effect of crash characteristics, a mixed ordered probit model with heterogeneity in the means and variances is applied to investigate motorcyclist injury severity in this paper. Initially, the model estimation introduces a utility function, Y_{in}^*, that determines the probability of rider injury severity outcome $\boldsymbol{i}$ in crash $\boldsymbol{n}$ which is written as (Washington et al., 2020),

$$Y_{in}^* = \beta_n \boldsymbol{X}_{in} + \varepsilon_{in} \tag{5.1}$$

where β_n is the vector of estimated parameters, $\boldsymbol{X}_{in}$ is the vector of explanatory variables, ε_{in} denotes the disturbance term which is assumed to be normally distributed with mean of zero and variance of one. For crash n, the drivers injury severity Y_n^* sustaining injury severity $\boldsymbol{i}$ can be defined as follow (Washington et al., 2020),

$$Y_n^* = i, if\ \mu_{i-1,n} \leq Y_n^* \leq \mu_{i,n} \tag{5.2}$$

where i (i = 0, 1, 2, respectively, for minor injury, severe injury and fatal injury), μ_i denotes the estimated threshold that corresponds to injury severity ordering and distinguishes the resulting severity categories in which is ordered in natures such that $\mu_{i-1} < \mu_i$. The ordered probability $P(y = i)$ of the i-th injury severity level for each individual crash observation is defined as (Washington et al., 2020),

$$P(y = i) = \Phi(\mu_i - \beta_n \boldsymbol{X}_n) - \Phi(\mu_{i+1} - \beta_n \boldsymbol{X}_n) \tag{5.3}$$

where $\Phi(.)$ denotes the cumulative standard normal distribution. A greater depth of accounting unobserved heterogeneity is to allow the possibility that the mean and variance of random parameters be influenced by other crash-level factors. This can be done by letting β_{in} be a vector of estimable parameters that varies across crash, which can be derived as follow (Seraneeprakarn et al., 2017),

$$\boldsymbol{\beta}_{in} = \beta_i + \boldsymbol{\psi}_{in} \boldsymbol{\Omega}_{in} + \sigma_{in} e^{(\boldsymbol{\gamma}_{im} \boldsymbol{\Psi}_{im})} \omega_{in}, \tag{5.4}$$

where β_i is the mean value of the random parameter vector, $\boldsymbol{\Omega}_{in}$ represent a vector of attributes that capture heterogeneity in mean that influence motorcyclist-injury severity level i, $\boldsymbol{\psi}_{in}$ is the corresponding vector of estimable parameters, $\boldsymbol{\Psi}_{im}$ is a vector of attributes that captures heterogeneity in the standard deviation σ_{in} with corresponding parameter vector $\boldsymbol{\gamma}_{im}$, and ω_{in} denotes a disturbance term. Halton sequence approach is used for a simulated maximum likelihood estimation process to make parameter estimation computationally efficient and reliable (Bhat, 2003). To achieve this, the paper estimated the models using maximum likelihood estimation with 1000 Halton draws (M. Islam and Mannering, 2020; Se et al., 2021a; Se et al., 2021b; Yan et al., 2022). As in previous studies (Al-Bdairi et al., 2020; Alnawmasi and Mannering, 2019; Alogaili and Mannering, 2022; Yan et al., 2022), normal distribution was considered for the function form of parameter density function, since it generally provides the best fit for data on injury severities. To ease the interpretation of the result, the present study also intends to compute the marginal effects to assess the effect of the explanatory variables on the probability of each injury-severity level in which the direction of the effects cannot be captured by the parameter estimates (Fountas and Anastasopoulos, 2017). Computationally, marginal effects are computed by the change in the resulting probability of each ordered outcome, due to a one-unit change in the explanatory variable (i.e., change from ‘‘0” to ‘‘1” in the case of indicator variables). In this study, marginal effects are computed by averaging over observations as follow (Fountas and Anastasopoulos, 2017; Washington et al., 2020):

$$\frac{P(y=i)}{\partial X} = [\,\Phi(\mu_{i-1} - \beta X) - \Phi(\mu_i - \beta X)]\beta \tag{5.5}$$

5.6 Likelihood Ratio Test

The likelihood ratio tests are well known for the application to examine the level of significant difference between sub-models (i.e., each sub-model using different sub-dataset). Two type of likelihood ratio test were frequently utilized by the previous research including the “*global instability test*” which is computed by comparing the log-likelihood based on the full data with the summation of log-likelihood based on all subgroup of data, and “*Pairwise instability test*” which is computed by directly comparing the parameters estimates of one subgroup with another subgroup of data to see whether they are significantly different (Alogaili and Mannering, 2022; Hou et al., 2022; Se et al., 2021b; Yan et al., 2022). Although the global test can be suggestive, the pair-wise test could potentially offer the better capability to thoroughly reveal the instability and nontransferability between subgroup of data (Hou et al., 2022). Therefore, the pairwise likelihood ratio test was used in this study to examine both temporal instability (yearly data) and transferability between daytime and nighttime data. This test requires out-of-sample estimation because the estimated parameters from one subgroup data are being used to estimate the log-likelihood of data from another subgroup data with these previously estimated parameters. Initially, the tests to see if motorcyclist injury severity models are statistically and significantly different between daytime and nighttime for each year from 2016 to 2019, a series of likelihood ratio tests were carried out with chi-square statistic,

$$X^2 = -2[LL(\beta_{T_2T_1})_t - LL(\beta_{T_1})_t] \tag{5.6}$$

where t denotes the year of the crashes happened (either 2016, 2017, 2018 or 2019), $LL(\beta_{T_2T_1})$ is the log-likelihood at convergence of the model estimated using converged parameters from T_2 (either daytime or nighttime) on data T_1(either daytime or nighttime, and $T_2 \neq T_1$), restricting the parameters to be T_2 estimated parameters. $LL(\beta_{T_1})$ is the log-likelihood at convergence of the D_1 model using T_1 data with parameters no longer restricted to T_2's converged parameters. The tests were also reversed, such that T_1 became T_2 and vice versa. To reject or accept the null hypothesis that the parameters are equal between T_1 and T_2 in particular year, the resulting value of X^2 is χ^2 distributed with a degree of freedom equal to the number estimated parameters, were used. The results of the tests are shown in **Table 5.3**, clearly elucidating that the null hypothesis that daytime and nighttime injury severity models are the same can be rejected with over 95% for each of the four years.

Lastly, another series of likelihood-ratio tests were performed to determine whether the separately estimated daytime model and separately estimated nighttime model were temporally stable over the four-year period. The chi-square-distributed test statistic can now be computed as follows:

$$X^2 = -2[LL(\beta_{Y_2 Y_1})_T - LL(\beta_{Y_1})_T] \quad (5.7)$$

where T denotes the time-of-day of the crashes happened (either daytime or nighttime), $LL(\beta_{Y_2 Y_1})$ is the log-likelihood at convergence of the model estimated using converged parameters from Y_2 (either 2016, 2017, 2018, or 2019) on data period Y_1 (either 2016, 2017, 2018, or 2019, and $Y_2 \neq Y_1$), restricting the parameters to be Y_2 estimated parameters. $LL(\beta_{Y_1})$ is the log-likelihood at convergence of the Y_1 model using Y_1 data with parameters no longer restricted to Y_2's converged parameters. The tests were also reversed, such that time period Y_1 became Y_2 and vice versa. **Table 5.4** shows the results of these tests and can be seen that majority of the two-year pair-wise test were identified as unequal with the null hypotheses (that the parameter estimates are the same and stable across the four-year considered period) being rejected at a high confidence level (19 out of 24 tests produce confidence levels of more than 99%), thus indicating high confidence that the estimated parameters are varying over time.

Table 5.3 Likelihood ratio test results between daytime and nighttime motorcyclist injury severity models for different years (Chi-square, degree of freedom in parenthesis and confidence level in bracket)

Years		T1 = Daytime	T1 = Nighttime
	T2 =	Nighttime	Daytime
2016		134.72 [17] (99.99%)	100.31 [21] (99.99%)
2017		31.93 [18] (97.76%)	61.17 [20] (99.99%)
2018		79.21 [23] (99.99%)	40.76 [25] (97.57%)
2019		62.72 [26] (99.99%)	112.81 [19] (99.99%)

Table 5.4 Temporal stability test results of daytime and nighttime motorcyclist injury severity models (Chi-square, degree of freedom in parenthesis and confidence level in bracket)

Y1/Y2	2016		2017		2018		2019	
	Daytime	Nighttime	Daytime	Nighttime	Daytime	Nighttime	Daytime	Nighttime
2016	-	-	89.53 [20] (99.99%)	113.55 [19] (99.99%)	***30.25 [25] (78.52%)***	98.73 [24] (99.99%)	102.91 [19] (99.99%)	92.73 [27] (99.99%)
2017	64.22 [21] (99.99%)	90.78 [18] (99.99%)	-	-	***11.28 [25] (0.85%)***	55.48 [24] (99.93%)	78.21 [19] (99.99%)	70.31 [27] (99.99%)
2018	74.09 [21] (99.99%)	64.96 [18] (99.99%)	70.51 [20] (99.99%)	71.58 [19] (99.99%)	-	-	117.83 [19] (99.99%)	55.62 [27] (99.90%)
2019	42.71 [21] (99.49%)	116.61 [18] (99.99%)	54.34 [20] (99.99%)	105.71 [19] (99.99%)	***28.38 [25] (70.96%)***	77.72 [24] (99.99%)	-	-

5.7 Result and Discussion

This section presents a discussion of selected variables and their effects on motorcyclist injury severity in daytime and nighttime crashes over considered study periods. **Table 5.5-5.6** display the estimation results for daytime and nighttime, respectively, in years 2016-2019 using a mixed ordered probit model with means and variances heterogeneity. It should be noted that, to seek heterogeneity that may arise from the fixed thresholds, this study also estimated the generalized ordered probit model in which the thresholds are allowed to vary as functions of exogenous variables (Eluru and Yasmin, 2015; Fountas and Anastasopoulos, 2017). However, these models produced lower statistical fit compared to their random parameter counterpart; therefore, the outputs of these models are not provided in the paper, also considering that the slightly different formulation of the generalized ordered probit models does not allow a straightforward comparison with the results of the models presented in this study (Fountas et al., 2021). To better illustrate the difference, the summary of the marginal effect of explanatory variables impacting motorcyclist injury severity are presented in **Table 5.7-5.8** to display such temporal variables for daytime and nighttime crash models, respectively. The remainder of the section presents the further discussion on the estimation results by variable category below.

5.7.1 Rider characteristics

As shown in **Table 5.5-5.6**, regarding gender of the rider, the results indicate there is no significant difference between gender-injury severities if the crashes happen during daytime. On the other hand, compared to female riders, the effect of male riders was unstable overtime for nighttime crashes (decreasing injury severity level in 2016 and increasing in 2018 and 2019; **Table 5.8**). This may be attributed to the possibility that, during nighttime, male may be more likely to take high risk to experience the excitement and thrill (an extrovert type) which may make them more vulnerable (Haque et al., 2010). Another reason may be due to the possibility that male riders are more likely to be aggressive, use excessively of alcohol, and have risky riding behavior (Se et al., 2022b; Yan et al., 2021b).

Compared to lone riders, the indicator for rider-with-pillion was statistically significant in all time periods (stable effect across 2016-2019) of both daytime and nighttime crashes, with their marginal effects increasing the likelihoods of fatal injury (**Table 5.7-5.8**). In addition, it produced significant random parameters in the 2017 daytime and 2019 daytime model (**Table 5.5**), with the majority of the observations increasing likelihood of fatal injury (see **Figure 5.4d** and **Figure 5.4m**, respectively**,** for distributional split of pillion random parameter). Multiple reasons may play a role in explaining these findings: 1) pillion may have peer influence on rider's risk-taking behaviors including excessive speed, aggressive riding or decision not to use a helmet etc. (Møller and Haustein, 2014), 2) additional weight distribution by pillion could alter the braking distance as well as increasing the impact (Alnawmasi and Mannering, 2019). Numerous studies also reported similar findings (Ijaz et al., 2021; Kashani et al., 2014; Savolainen and Mannering, 2007).

Interestingly, variable reflecting exceeding speed limit produced only random parameter in 2017 daytime, 2018 daytime and 2019 nighttime. This may be attributed to that majority of the motorcycle crashes in the current study identified speeding as the cause and also contained a relatively high proportion of minor injuries; therefore, speeding-related crashes are likely to result in unobserved heterogeneity (previous works also reported similar finding (Anastasopoulos and Mannering, 2016; Se et al., 2022a)). For daytime, as seen in **Figure 5.4e** and **Figure 5.4i**, 39.35% and 49.14% of the observations increase the likelihood of fatal injury for 2017 and 2018, respectively (the rest of the observations decrease injury severity). However, for nighttime crashes, the majority of the observations (65.62%) were found to increase the likelihood of fatal injury (**Figure 5.5k)**. This finding indicates that while the significant proportion of the rider involving speeding-crash had a high probability of sustaining fatal injury, speeding-related crashes occurring during nighttime seem to be a more serious safety issue, which may be attributed to low visibility causing shorter stopping sight distance that do not allow the riders to effective slow down before the crash. A possible reason that this indicator became significant during a later period, may be partially due to changes (or may be an improvement of accuracy/correctness) in police-reporting practices over time, which more frequently identify speeding as the cause of severe crashes. Although without mentioning time-of-day, previous studies also confirm the findings (Alnawmasi and Mannering, 2019; Ijaz et al., 2021; M. S. Shaheed and Gkritza, 2014; Xin et al., 2017).

The indicator for riders hitting an unexpected crossing object produced random parameters in both 2018 daytime and nighttime crash models. For daytime, 60.93% of hitting-crossing-object crashes increase the likelihood of fatal injury (**Figure 5.4j)**; whereas, during nighttime, 94.08% of hitting-crossing-object had a higher probability of minor injury (**Figure 5.5f**). This indicator also produced a fixed effect in the 2019 daytime model, with the marginal effect increasing the likelihood of minor injury (**Table 5.7**). However, potential source of the observed instability and unobserved heterogeneity is not necessarily clear, but likely due to other possible unmeasured factors such as type of the objects and crash mechanism etc.

Indicator for rider overtaking other vehicles illegally, was found statistically significant in only day time model (2016, 2017 and 2018), with stable average marginal effect increasing the likelihood of fatal injury (with striking magnitude of marginal effect [0.19336, 0.16662 and 0.29066, respectively]; **Table 5.7**). It was not found significant in the nighttime model which may be attributed to that riders maybe more likely to decide to overtake regardless a greater risk because they have full visibility (i.e., risk compensation); however, during nighttime with limited visual, riders may be more careful in their decision of overtaking.

Lastly, indicator for fatigued riders was significant in only 2016 daytime (insignificant in all later period), with the strikingly high effect increasing the likelihood of minor injury (**Table 5.7**). In contrast, this indicator was statistically significant in three nighttime models including 2016, 2017 and 2019. In addition, it generated the stable and significantly high average marginal effect that increased the likelihoods of fatal injury (0.22736, 0.42826 and 0.22972, respectively; **Table 5.8**). This finding is intuitive since riders are more likely to be tired and fatigued during nighttime compared to daytime riding and the increasing probability of higher injury severity may be due to reduction in reaction time, alertness and ability to control the motorcycle to maintain safer situations. Several studies also confirm this result (Se et al., 2021a; Se et al., 2022b).

Table 5.5 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for daytime motorcyclist injury severity (bolds indicate random parameter)

	2016		2017		2018		2019	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Rider characteristics								
Pillion	0.161 **	2.53	**0.793** ***	**6.06**	0.275 ***	3.76	**0.242** ***	**3.43**
SD "Pillion"			**0.533** ***	**9.47**			**0.825** ***	**9.97**
Exceeding speed limit			**-0.253** **	**-1.99**	**-0.028**	**-0.13**		
SD "Exceeding speed limit"			**0.936** ***	**17.99**	**1.301** ***	**21.87**		
Hit a crossing object					**0.382**	**1.52**	-0.126 *	-1.94
SD "Hit a crossing object"					**1.377** ***	**17.40**		
Illegal overtaking	0.652 ***	3.01	0.657 ***	2.81	1.205 ***	4.26		
Fatigue	-0.889 **	-2.10						
Roadway characteristics								
Frontage lane	-0.448 **	-2.46	-1.554 ***	-6.62	-0.969 ***	-4.55		
Work zone			-0.406 *	-1.90			**-0.339**	**-1.20**
SD "Work zone"							**1.339** ***	**2.78**
2 Lanes	0.649 ***	5.07					2.210 ***	4.92
4 Lanes	0.413 ***	4.18					0.382 ***	4.09

Table 5.5 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for daytime motorcyclist injury severity (bolds indicate random parameter) (Cont.)

	2016		2017		2018		2019	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Flush median			0.873 **	2.09	0.742 **	2.34		
Raised median	-0.189	-1.16					-0.171 **	-2.11
SD "Raised median"	1.377 ***	13.68						
Depressed median			0.748 *	1.70	0.590 ***	3.76		
SD "Depressed median"			0.497 ***	6.19				
Barrier median	-0.343 **	-2.13					-0.476 ***	-3.21
Concrete road			-0.258 **	-2.18	-0.309 ***	-2.76		
Curve	0.260 **	2.49						
Grade					0.522 ***	2.89	0.350 *	1.83
4-leg intersection					0.755 ***	4.76		
3-leg intersection							-0.219 *	-1.81
U-turn	0.373 ***	3.43					0.341 ***	2.95
Bridge					0.622 **	2.03		
Urban road	-0.277 ***	-3.38	-0.751 ***	-3.73	-0.473 ***	-5.17	-0.133 *	-1.66
SD "Urban road"			1.283 ***	11.15				

Table 5.5 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for daytime motorcyclist injury severity (bolds indicate random parameter) (Cont.)

	2016		2017		2018		2019	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Environmental characteristics								
Raining					1.670 ***	2.64		
Weekend	0.257 ***	2.74	0.438 ***	4.52	0.254 ***	2.64	0.382 ***	3.83
Crash characteristics								
Hit a motorcycle	-0.490 ***	-4.67	-0.724 ***	-5.93	-0.467 ***	-3.57	-0.525 ***	-4.62
Hit a pickup truck	0.220 **	2.56	**-0.275** *	**-1.78**	0.339 ***	3.20		
SD "Hit a pickup truck"			**1.003** ***	**14.22**				
Hit a van/minibus	0.499 ***	3.53	0.362 **	2.53	0.663 ***	3.84		
Hit a truck	**0.818** ***	**3.94**	1.204 ***	9.38	1.701 ***	11.65	0.846 ***	7.36
SD "Hit a truck"	**1.248** ***	**8.61**						
Rear-end crash	-0.287 ***	-3.41			-0.755 ***	-5.31		
Sideswipe crash	**-0.336** ***	**-2.77**	-0.180 *	-1.81	**-1.689** ***	**-8.10**	-0.308 ***	-2.71
SD "Sideswipe crash"	**0.750** ***	**10.80**			**1.048** ***	**13.92**		
Single-motorcycle crash	-0.271 ***	-2.62			-0.500 ***	-3.05	**-0.505** ***	**-3.68**
SD "Single-motorcycle crash"							**0.742** ***	**4.42**

Table 5.5 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for daytime motorcyclist injury severity (bolds indicate random parameter) (Cont.)

	2016		2017		2018		2019	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Head on crash			0.391 ***	2.63	**-0.439**	**-1.06**	0.266 *	1.87
SD "Head on crash"					**1.029 *****	**9.00**		
Heterogeneity in mean								
Raised median : Exceeding speed limit	-0.496 ***	-3.08						
Hit a truck : Flush median	2.486 ***	3.16						
Pillion : Gender			-0.329 **	-2.40				
Pillion : Alcohol			-0.329 **	-2.52				
Depressed median : Alcohol			0.639 ***	3.52				
Exceeding speed limit : 2 Lanes					0.422 *	1.67		
Hit a crossing object : Flush median					-0.953 ***	-2.75		
Sideswipe crash : 2 Lanes					0.509 **	2.45		
Sideswipe crash : 4 Lanes					0.626 ***	3.05		
Work zone : Depressed median							2.332 **	2.36
Heterogeneity in variance								

Table 5.5 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for daytime motorcyclist injury severity (bolds indicate random parameter) (Cont.)

	2016		2017		2018		2019	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Exceeding speed limit : Main lane			-2.884 ***	-13.81				
Hit a pickup truck : Main lane			3.812 ***	11.88				
Urban road : Main lane			-2.414 ***	-10.47				
Exceeding speed limit : Wet road					0.530 ***	3.22		
Hit a crossing object : Wet road					2.076 ***	7.60		
Sideswipe crash : Wet road					13.208 ***	44.49		
Work zone : Exceeding speed limit							0.870 *	1.80
Single-motorcycle crash : Exceeding speed limit							1.512 ***	6.08
Threshold								
μ	0.844 ***	23.64	0.990 ***	23.71	0.990 ***	22.41	0.730 ***	23.33
Model fit statistic								
Log-likelihood at constant	-2054.083		-1995.107		-2113.879		-2167.074	
Log-likelihood at convergence	-1853.152		-1818.181		-1919.764		-1999.817	
ρ^2	0.0978		0.0887		0.0918		0.0772	

Table 5.6 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for nighttime motorcyclist injury severity (bolds indicate random parameter)

	2016		2017		2018		2019	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Rider characteristics								
Gender	-0.355 **	-2.47			0.457 ***	5.10	0.417 ***	4.16
Pillion	0.281 ***	3.24	0.198 **	2.27	0.112 *	1.66	0.368 ***	4.48
Exceeding speed limit							**0.396** ***	**3.56**
SD "Exceeding speed limit"							**0.985** ***	**17.70**
Hit a crossing object					**-0.253**	**-1.63**		
SD "Hit a crossing object"					**0.162** *	**1.93**		
Fatigue	0.848 **	2.21	1.423 ***	2.58			0.739 **	2.09
Roadway characteristics								
Frontage lane	-0.400 *	-1.87	**-1.780** ***	**-5.22**	-1.088 ***	-5.57		
SD "Frontage lane"			**1.334** ***	**3.10**				
Work zone							0.587 ***	2.65
2 Lanes	0.674 ***	3.92			1.575 ***	3.13	2.593 ***	4.61
4 Lanes	**-0.850** ***	**-3.95**			0.179 *	1.73	0.365 ***	3.57
SD "4 Lanes"	**0.597** ***	**8.18**						

Table 5.6 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for nighttime motorcyclist injury severity (bolds indicate random parameter) (Cont.)

	2016			2017			2018			2019		
	Coefficient		t-Stat	Coefficient		t-Stat	Coefficient		t-Stat	Coefficient		t-Stat
Flush median				0.443	***	3.15	0.318	***	2.63			
Raised median							0.279	***	2.91			
Depressed median				0.249	*	1.71						
SD "Depressed median"				0.770	***	4.51						
Concrete road	**0.288**	**	**2.47**				-0.274	**	-2.32			
SD "Concrete road"							0.749	***	6.26			
Grade	**0.564**	**	**2.42**	0.444	*	1.73						
3-leg intersection							0.264	*	1.83			
U-turn	**0.461**	***	**3.28**									
Bridge				0.970	**	2.18				1.127	***	2.74
Urban road				-0.159	*	-1.67	-0.199	**	-2.16	-0.242	**	-1.96
SD “Urban road”										0.782	***	7.33
Environmental characteristics												
Wet road	0.829	***	2.93	0.808	***	2.72	1.261	***	4.54	0.631	**	2.40
Raining							-0.787	***	-2.75	**-0.294**		**-1.25**

Table 5.6 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for nighttime motorcyclist injury severity (bolds indicate random parameter) (Cont.)

	2016		2017		2018		2019	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
SD "Raining"							**1.142** ***	**6.13**
Weekend			0.606 ***	5.56	0.235 **	2.49		
Unlit	0.357 ***	3.91	0.174 **	2.02	0.209 **	2.57	0.274 ***	3.22
Crash characteristics								
Hit a motorcycle	-0.391 ***	-2.64	-0.381 ***	-2.83	-0.387 ***	-2.79	-0.815 ***	-5.32
Hit a passenger car			-0.216 **	-2.21	-0.251 **	-2.21	-0.239 **	-2.08
Hit a pickup truck	**0.056**	**0.21**	**0.020**	**0.14**	**0.372** ***	**3.09**		
SD "Hit a pickup truck"	**0.722** ***	**6.39**	**1.058** ***	**6.44**	**0.620** ***	**7.56**		
Hit a van/minibus					**0.258**	**1.21**	0.464 **	2.01
SD "Hit a van/minibus"					**1.358** ***	**5.13**		
Hit a truck	0.945 ***	6.70	0.780 ***	5.70	0.981 ***	6.81	**1.352** ***	**7.91**
SD "Hit a truck"							**0.343** ***	**2.63**
Rear-end crash							-0.447 ***	-3.05
Sideswipe crash	-0.528 ***	-4.18			**-0.274** *	**-1.92**	-0.494 ***	-3.22
SD "Sideswipe crash"					**0.693** ***	**7.75**		

Table 5.6 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for nighttime motorcyclist injury severity (bolds indicate random parameter) (Cont.)

	2016		2017		2018		2019	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Single-motorcycle crash							-0.522 ***	-3.35
Head on crash	0.525 ***	2.64	0.688 ***	3.80	0.380 **	2.22	0.456 **	2.44
Heterogeneity in mean								
4 lanes : Hit a crossing object	0.768 ***	3.53						
Hit a pickup truck : Hit a crossing object	0.400 *	1.65						
Frontage lane : Alcohol			3.806 ***	3.75				
Frontage lane : Raised median			2.221 ***	2.71				
Depressed median : Alcohol			-0.676 *	-1.87				
Hit a crossing object : Curve					0.889 **	2.11		
Hit a pickup truck : Curve					2.344 ***	3.50		
Sideswipe crash : Curve					-1.511 **	-2.51		
Urban road : Barrier median							-0.864 ***	-3.33
Raining : Concrete road							-1.192 **	-2.44
Raining : Curve							-1.308 **	-2.41

Table 5.6 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for nighttime motorcyclist injury severity (bolds indicate random parameter) (Cont.)

	2016		2017		2018		2019	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Raining : U-turn							1.449 **	2.07
Hit a truck : Barrier median							-0.845 **	-2.01
Hit a truck : Concrete road							-0.831 **	-2.06
Hit a truck : U-turn							-2.137 *	-1.84
Heterogeneity in variance								
4 lanes : Rear-end crash	0.923 ***	5.73						
Depressed median : Exceeding speed limit			-1.363 ***	-5.21				
Hit a pickup truck : Exceeding speed limit			3.315 ***	16.98				
Concrete road : Depressed median					1.783 ***	4.88		
Hit a pickup truck : Depressed median					-1.627 ***	-4.32		
Sideswipe crash : Depressed median					2.392 ***	7.76		

Table 5.6 Estimation results of mixed ordered probit model with heterogeneity in the means and variances for nighttime motorcyclist injury severity (bolds indicate random parameter) (Cont.)

	2016			2017			2018			2019		
	Coefficient		t-Stat	Coefficient		t-Stat	Coefficient		t-Stat	Coefficient		t-Stat
Exceeding speed limit : Frontage lane										-0.927	*	-1.87
Raining : Alcohol										1.021	*	1.84
Urban road : Alcohol										-2.597	***	-6.57
Threshold												
μ	0.705	***	17.67	0.670	***	17.57	0.681	***	19.34	0.677	***	17.71
Model fit statistic												
Log-likelihood at constant			-1387.194			-1357.652			-1600.863			-1563.527
Log-likelihood at convergence			-1202.744			-1228.335			-1429.287			-1373.630
ρ2			0.1330			0.0953			0.1072			0.1215

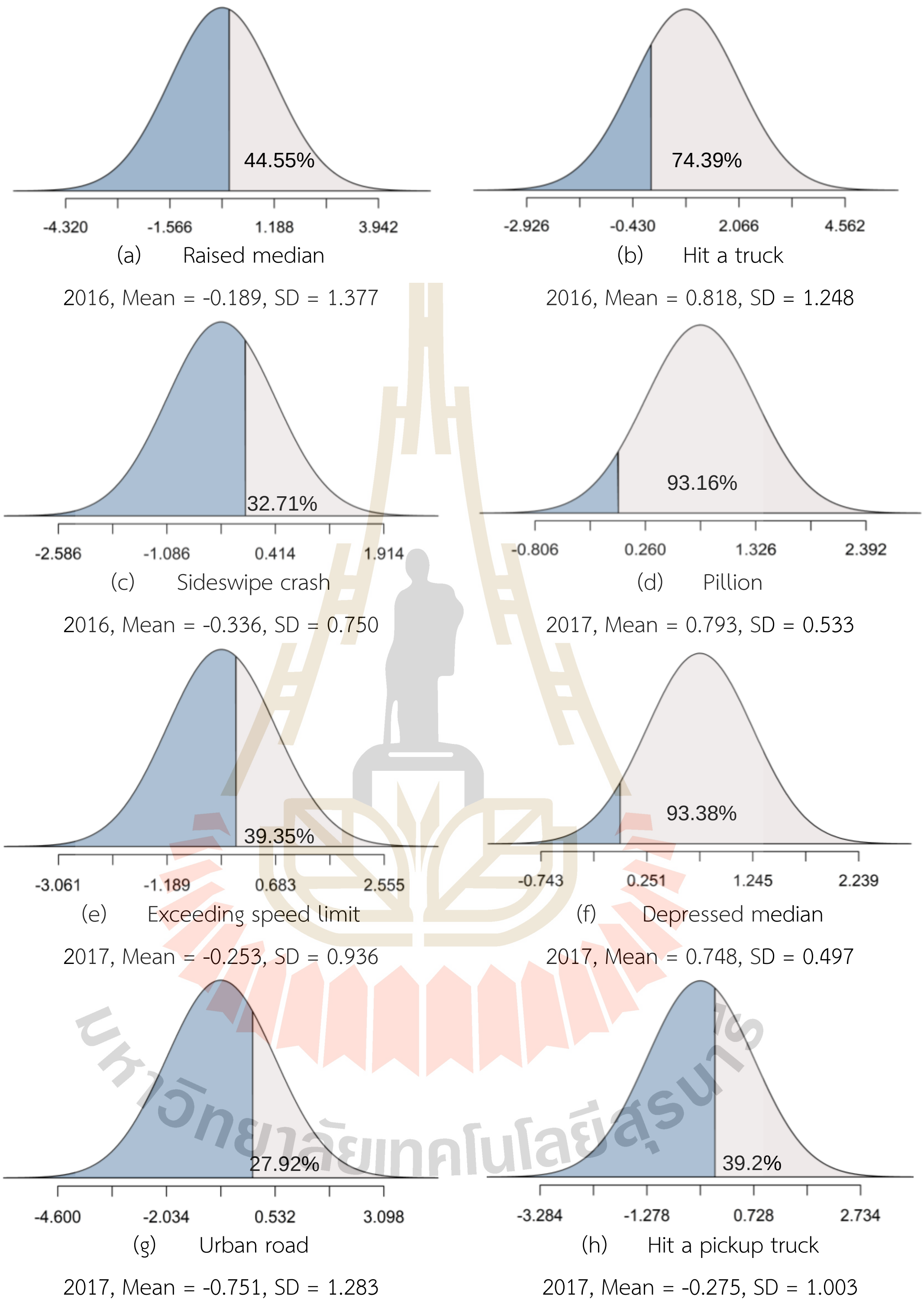
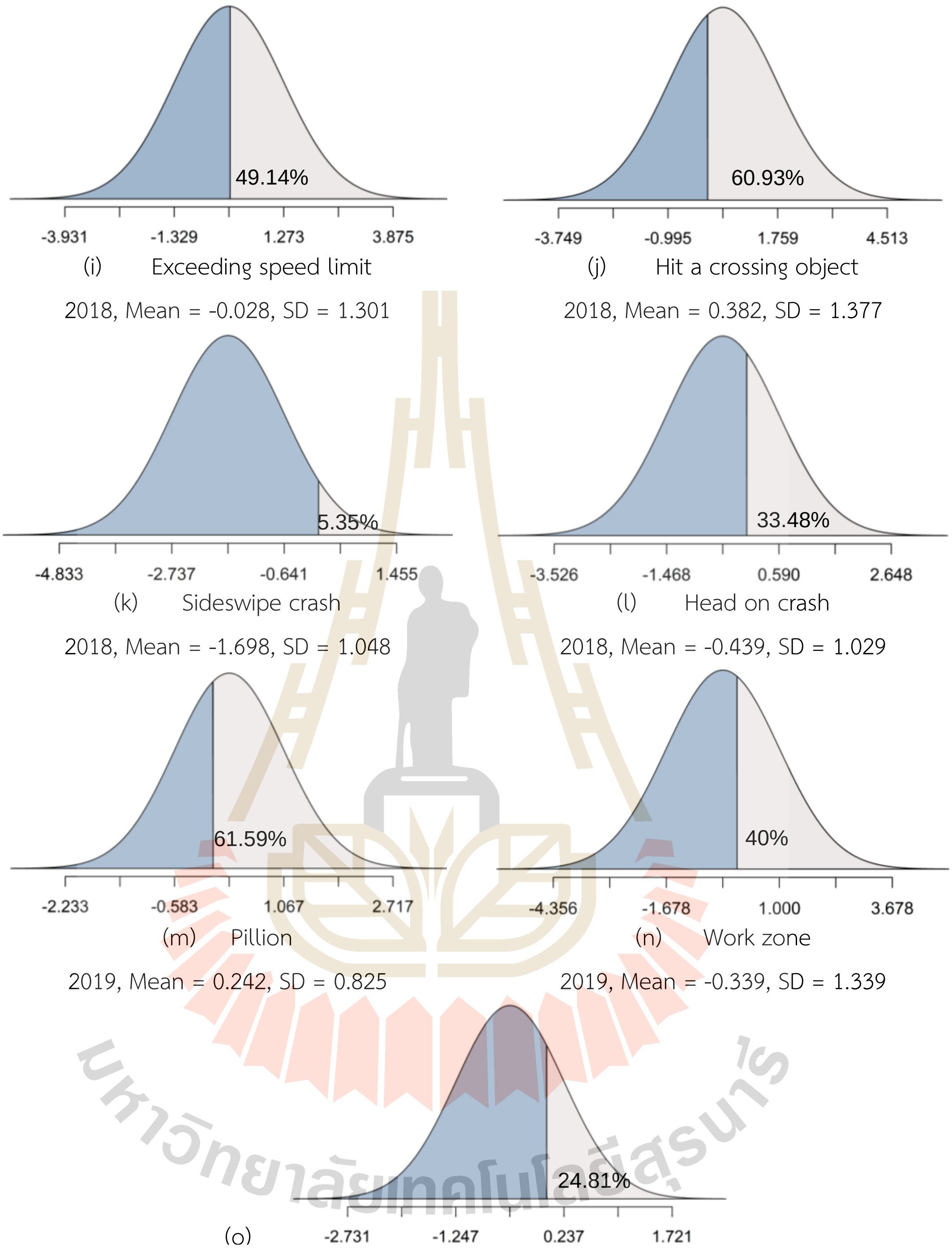


Figure 5.4 Distributional characteristics of random parameters in daytime crash models



(i) Exceeding speed limit

2018, Mean = -0.028, SD = 1.301

(j) Hit a crossing object

2018, Mean = 0.382, SD = 1.377

(k) Sideswipe crash

2018, Mean = -1.698, SD = 1.048

(l) Head on crash

2018, Mean = -0.439, SD = 1.029

(m) Pillion

2019, Mean = 0.242, SD = 0.825

(n) Work zone

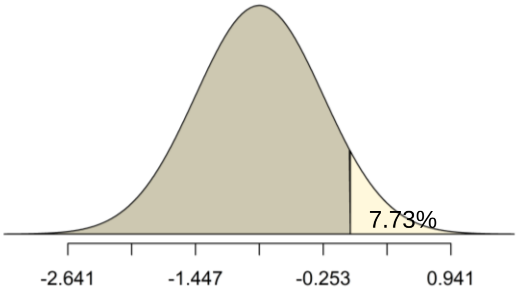
2019, Mean = -0.339, SD = 1.339

(o)

(p) Single-motorcycle crash

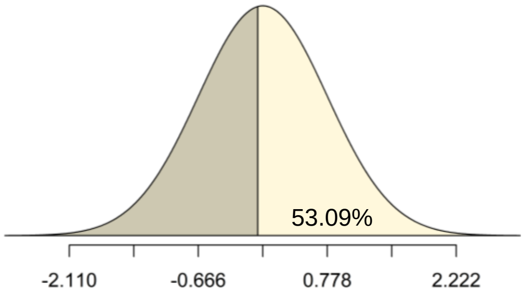
2019, Mean = -0.505, SD = 0.742

Figure 5.4 Distributional characteristics of random parameters in daytime crash models (Cont.)



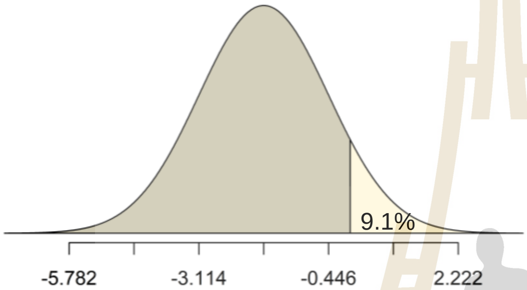
(a) 4 Lanes

2016, Mean = -0.850, SD = 0.597



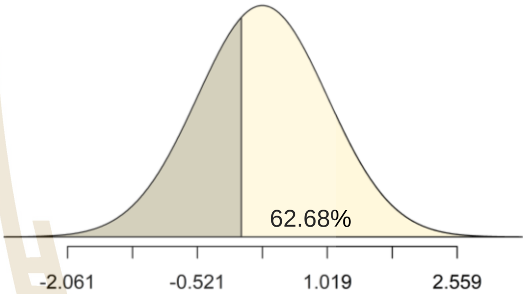
(b) Hit a pickup truck

2016, Mean = 0.056, SD = 0.722



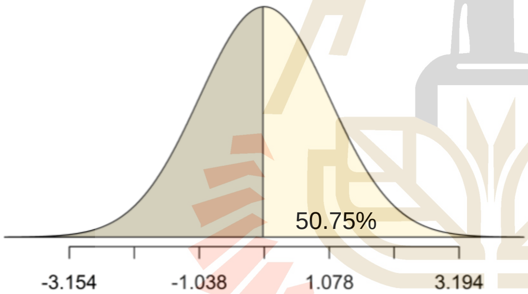
(c) Frontage lane

2017, Mean = -1.780, SD = 1.334



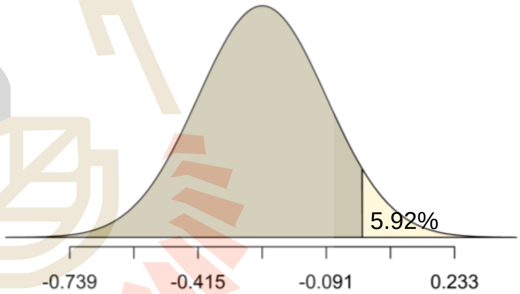
(d) Depressed median

2017, Mean = 0.249, SD = 0.770



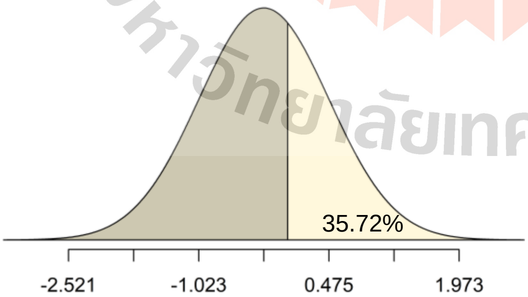
(e) Hit a pickup truck

2017, Mean = -0.020, SD = 1.058



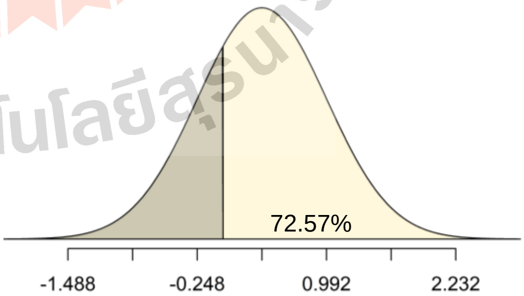
(f) Hit a crossing object

2018, Mean = -0.253, SD = 0.162



(g) Concrete road

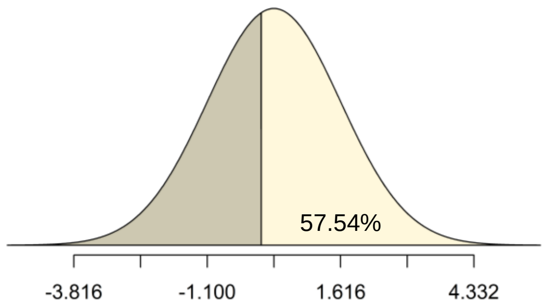
2018, Mean = -0.274, SD = 0.749



(h) Hit a pickup truck

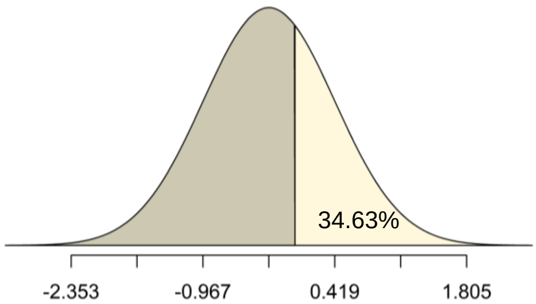
2018, Mean = 0.372, SD = 0.620

Figure 5.5 Distributional characteristics of random parameters in nighttime crash models



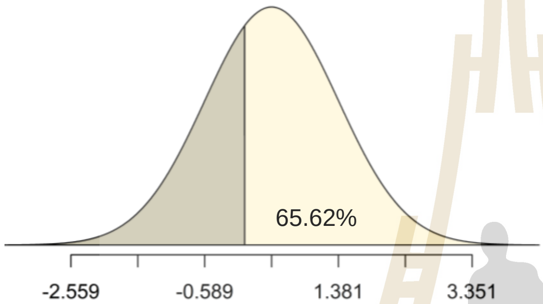
(i) Hit a van/minibus

2018, Mean = 0.258, SD = 1.358



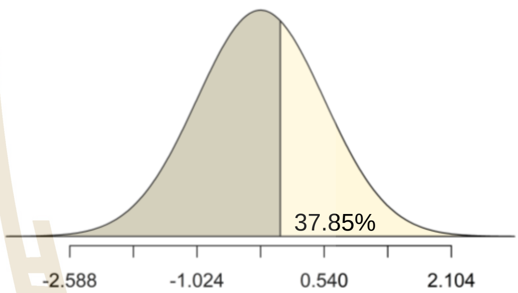
(j) Sideswipe crash

2018, Mean = -0.274, SD = 0.693



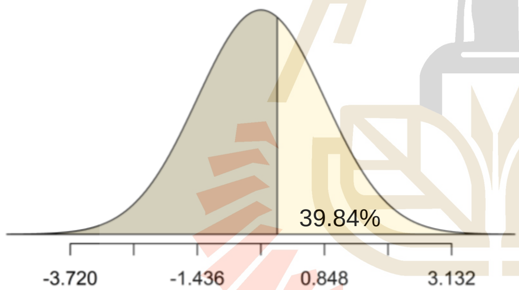
(k) Exceeding speed limit

2019, Mean = 0.396, SD = 0.985



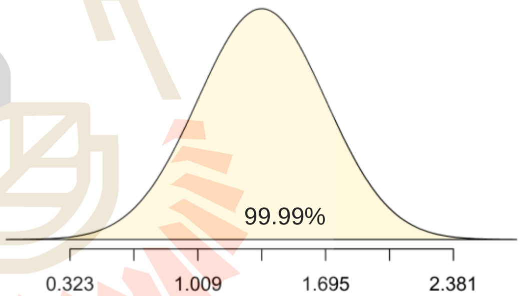
(l) Urban road

2019, Mean = -0.242, SD = 0.782



(m) Raining

2019, Mean = -0.294, SD = 1.142



(n) Hit a truck

2019, Mean = 1.352, SD = 0.343

Figure 5.5 Distributional characteristics of random parameters in nighttime crash models (Cont.)

5.7.2 Roadways characteristics

Indicator for crash on frontage lane was significant in 2016-2018 daytime and nighttime period, with the stable and consistent average marginal effect increasing the likelihood of minor injury severity (**Table 5.7-5.8**). It should be noted that this indicator produced random parameter in the 2017 nighttime model, with 90.9% of the observations increasing the likelihood of minor injury (**Figure 5.5c**). Past research (Se et al., 2021a; Xin et al., 2017) also confirm the finding. Possible explanation may be attributed to that frontage lanes are built to serve just local traffic, low speed and low traffic volume.

Indicator for work zone crash was significant in 2017 daytime and 2019 both daytime and nighttime. While work zone crashes had higher probability of minor injury in the 2017 daytime model, this indicator produced random parameter in 2019 daytime (with 40% of the observation increased the likelihood of fatal injury [**Figure 5.4n**]) and resulted in fixed-effects in the 2019 nighttime model with the effect increasing the likelihood of fatal injury. From one year to the next, work zones also change from one location to another location and may be controlled by different contractors which may have different safety control quality. This could be used to explain the observed temporal instability across time periods found in this study. Interestingly, in both daytime and nighttime of 2019, work zone crashes increased the probability of fatal injury, indicating that the safety control quality in that particular year was not safe enough to prevent severe motorcycle crashes.

Compared to crashes on 6 or more lanes, 2 lanes and 4 lanes road crashes were found statistically significant in 2016 and 2019 daytime, and 2016, 2018 and 2019 nighttime (Note: this indicator produced random parameter in the 2016 nighttime model [see **Figure 5.5a**]), with their stable average marginal effect increasing the likelihood of fatal injury (**Table 5.7-5.8**). This may be attributed to that lower number of lanes roads are normally undivided road (particularly 2 lane road) with the nature that are likely to encourage dangerous crash type such as head on crash and high-speed crash (particularly rural area). It should be noted that the magnitude of fatal injury marginal effect of 2 lanes indicator is strikingly high which potentially deserved more safety attention. Regarding road median types (**Table 5.7-5.8**), indicator for crashes on flush median was statistically significant in the 2017-2018 daytime and nighttime model, with stable average marginal effect increasing the likelihoods of fatal injury, compared to other median types. Several studies also confirmed this finding (Se et al., 2021a; Se et al., 2022b). Indicator for raised median crash was significant in 2016 and 2019 daytime, with their average marginal effects increasing the likelihood of minor injury (note: it produced random parameter in 2016 [see distributional split in Figure 5.4a]).

Table 5.7 Summary of marginal effect for daytime motorcyclist injury severity model (bold values indicate random parameter)

	2016			2017			2018			2019		
	Minor	Severe	Fatal	Minor	Severe	Fatal	Minor	Severe	Fatal	Minor	Severe	Fatal
Rider characteristics												
Pillion	-0.05465	0.01378	0.04087	**-0.24995**	**0.06445**	**0.18550**	-0.07840	0.02910	0.04930	**-0.08534**	**0.01479**	**0.07055**
Exceeding speed limit				**0.07823**	**-0.02437**	**-0.05385**	**0.00798**	**-0.00309**	**-0.00489**			
Hit a crossing object							**-0.10949**	**0.03956**	**0.06993**	0.04423	-0.00891	-0.03533
Illegal overtaking	-0.21507	0.02171	0.19336	-0.19793	0.03131	0.16662	-0.33900	0.04835	0.29066			
Fatigue	0.26971	-0.11520	-0.15451									
Roadway characteristics												
Frontage lane	0.14894	-0.05351	-0.09544	0.37379	-0.19883	-0.17496	0.23180	-0.11681	-0.11499			
Work zone				0.12144	-0.04735	-0.07409				**0.11768**	**-0.03100**	**-0.08668**
2 Lanes	-0.21738	0.04860	0.16877							-0.47721	-0.02877	0.50598
4 Lanes	-0.14059	0.03572	0.10486							-0.13508	0.02516	0.10992
Flush median				-0.25221	0.03270	0.21951	-0.21775	0.06235	0.15540			
Raised median	**0.06417**	**-0.01863**	**-0.04554**							0.06015	-0.01272	-0.04743
Depressed median				**-0.21897**	**0.03825**	**0.18072**	-0.17140	0.05493	0.11646			
Barrier median	0.11628	-0.03914	-0.07713							0.16482	-0.04704	-0.11777
Concrete road				0.07862	-0.02831	-0.05031	0.08475	-0.03629	-0.04846			
Curve	-0.08890	0.01928	0.06962									
Grade							-0.15210	0.04567	0.10642	-0.12186	0.01331	0.10855
4-leg intersection							-0.22038	0.05542	0.16495			
3-leg intersection										0.07671	-0.01807	-0.05864
U-turn	-0.12669	0.02394	0.10275							-0.11896	0.01421	0.10476

Table 5.7 Summary of marginal effect for daytime motorcyclist injury severity model (bold values indicate random parameter) (Cont.)

	2016			2017			2018			2019		
	Minor	Severe	Fatal	Minor	Severe	Fatal	Minor	Severe	Fatal	Minor	Severe	Fatal
Bridge							-0.18107	0.04929	0.13178			
Urban road	0.09488	-0.02959	-0.06529	**0.22469**	**-0.09672**	**-0.12798**	0.12893	-0.05708	-0.07185	0.04687	-0.01004	-0.03683
Environmental characteristics												
Raining							-0.44875	0.02246	0.42629			
Weekend	-0.08650	0.02055	0.06595	-0.13368	0.03683	0.09685	-0.07202	0.02625	0.04577	-0.13268	0.01993	0.11275
Crash characteristics												
Hit a motorcycle	0.16440	-0.05697	-0.10744	0.21089	-0.08595	-0.12494	0.12538	-0.05547	-0.06991	0.18105	-0.05021	-0.13084
Hit a pickup truck	-0.07538	0.01871	0.05667	**0.08437**	**-0.02835**	**-0.05602**	-0.09669	0.03579	0.06090			
Hit a van/minibus	-0.16761	0.02564	0.14197	-0.11140	0.02689	0.08451	-0.19247	0.05219	0.14028			
Hit a truck	**-0.27021**	**0.02198**	**0.24822**	-0.34934	0.01285	0.33649	-0.46862	0.02854	0.44008	-0.28409	-0.00101	0.28510
Rear-end crash	0.09661	-0.02735	-0.06926				0.19541	-0.07178	-0.12363			
Sideswipe crash	**0.11339**	**-0.03464**	**-0.07874**	0.05525	-0.01859	-0.03666	**0.40455**	**-0.18468**	**-0.21987**	0.10828	-0.02417	-0.08411
Single-motorcycle crash	0.09069	-0.02726	-0.06344				0.13384	-0.05583	-0.07802	**0.17597**	**-0.04576**	**-0.13021**
Head on crash				-0.12047	0.02831	0.09216	**0.11538**	**-0.04888**	**-0.06650**	-0.09361	0.01294	0.08067

Table 5.8 Summary of marginal effect for nighttime motorcyclist injury severity model (bold values indicate random parameter)

	2016			2017			2018			2019		
	Minor	Severe	Fatal	Minor	Severe	Fatal	Minor	Severe	Fatal	Minor	Severe	Fatal
Rider characteristics												
Gender	0.10470	-0.01870	-0.08600				-0.14906	0.00716	0.14191	-0.13085	0.01002	0.12082
Pillion	-0.08231	0.01664	0.06566	-0.06263	-0.00202	0.06465	-0.03498	-0.00134	0.03633	-0.11019	-0.00224	0.11243
Exceeding speed limit										**-0.12311**	**0.00526**	**0.11785**
Hit a crossing object							**0.08125**	**-0.00105**	**-0.08020**			
Fatigue	-0.24631	0.01894	0.22736	-0.31402	-0.11425	0.42826				-0.19784	-0.03188	0.22972
Roadway characteristics												
Frontage lane	0.11242	-0.03048	-0.08194	**0.52341**	**-0.15451**	**-0.36891**	0.35440	-0.06646	-0.28794			
Work zone										-0.16397	-0.02008	0.18405
2 Lanes	-0.21209	0.04461	0.16748				-0.38236	-0.04330	0.42566	-0.43199	-0.05874	0.49073
4 Lanes	**0.25395**	**-0.06914**	**-0.18481**				-0.05633	-0.00188	0.05821	-0.11189	0.00023	0.11166
Flush median				-0.13316	-0.01370	0.14686	-0.09900	-0.00283	0.10182			
Raised median							-0.08920	0.00002	0.08918			
Depressed median				**-0.07759**	**-0.00413**	**0.08172**						
Concrete road	-0.08404	0.01545	0.06859				**0.08894**	**-0.00211**	**-0.08683**			
Grade	-0.16672	0.02126	0.14546	-0.13154	-0.01631	0.14784						
3-leg intersection							-0.07991	-0.00685	0.08676			
U-turn	-0.13509	0.02063	0.11446									
Bridge				-0.24784	-0.06495	0.31279				-0.27067	-0.07049	0.34116
Urban road				0.05151	-0.00064	-0.05087	0.06385	-0.00030	-0.06354	**0.07548**	**-0.00361**	**-0.07187**

Table 5.8 Summary of marginal effect for nighttime motorcyclist injury severity model (bold values indicate random parameter) (Cont.)

	2016			2017			2018			2019		
	Minor	Severe	Fatal	Minor	Severe	Fatal	Minor	Severe	Fatal	Minor	Severe	Fatal
Environmental characteristics												
Wet road	-0.24284	0.02175	0.22109	-0.22436	-0.04185	0.26621	-0.29889	-0.09347	0.39235	-0.17536	-0.02199	0.19735
Raining							0.25115	-0.03307	-0.21808	**0.09117**	**-0.00607**	**-0.08510**
Weekend				-0.18391	-0.00928	0.19318	-0.07270	-0.00357	0.07626			
Unlit	-0.10738	0.02156	0.08582	-0.05523	-0.00165	0.05688	-0.06506	-0.00334	0.06840	-0.08316	-0.00130	0.08446
Crash characteristics												
Hit a motorcycle	0.10979	-0.02843	-0.08136	0.12500	-0.00729	-0.11771	0.12633	-0.00577	-0.12055	0.25650	-0.03570	-0.22080
Hit a passenger car				0.07038	-0.00113	-0.06925	0.08103	-0.00054	-0.08049	0.07419	-0.00299	-0.07120
Hit a pickup truck	**-0.01634**	**0.00344**	**0.01290**	**-0.00636**	**-0.00010**	**0.00645**	**-0.11405**	**-0.00907**	**0.12311**			
Hit a van/minibus							**-0.07780**	**-0.00682**	**0.08462**	-0.13290	-0.01211	0.14501
Hit a truck	-0.28214	0.02494	0.25721	-0.22236	-0.04230	0.26466	-0.26013	-0.06781	0.32794	**-0.32405**	**-0.10018**	**0.42423**
Rear-end crash										0.13490	-0.00596	-0.12894
Sideswipe crash	0.14972	-0.04174	-0.10798				0.08839	-0.00111	-0.08728	0.15410	-0.01150	-0.14260
Single-motorcycle crash										0.15954	-0.00511	-0.15443
Head on crash	-0.15547	0.02147	0.13400	-0.19416	-0.03466	0.22881	-0.11366	-0.01297	0.12663	-0.13250	-0.01149	0.14399

In contrast, this indicator was found significant in 2018 nighttime, with the effect increasing the likelihood of fatal injury. This indicates a strong nontransferability between daytime and nighttime regarding the effect of raised median. Possible reason may be that raised median is normally built for urban area where self-selectivity of nighttime riders and surrounding environment are different from daytime riders (for examples: trip purposes, speed selection, traffic volume, visual condition, etc.,). Indicator for depressed median road crash was found statistically significant in 2017 daytime/nighttime and 2018 daytime, with their consistent average marginal effects increasing the likelihood of fatal injury. Note that depressed median indicator produced random parameter in both 2017 daytime and nighttime (see their distributional splits in **Figure 5.4f** and **Figure 5.5d**). This finding is also supported by reasonable explanation that depressed medians are normally for rural road where it served mixed- and high-speed traffics (Champahom et al., 2022; Se et al., 2022b). Lastly, indicator for crashes on barrier median road was statistically significant in 2016 and 2019 daytime model, with consistent average marginal effect decreasing the likelihoods of severe and fatal injury. Possible explanation may be that the barrier median may restrict the turning option and redirect this action to a safer location, thereby reducing the risk of a head-on collision and other unsafe/illegal overtaking (Se et al., 2021a).

As compared to crashes on asphalt pavement, indicator for crashes on concrete pavement was found statistically significant in 2017 and 2018 daytime, with average marginal effect increasing the likelihood of minor injury. On the contrary, for nighttime model, crash on concrete road increase the possibility of fatal injury in 2016 and increase likelihoods of fatal injury for 35.72% of the observation in 2018 (see **Figure 5.5g**). Again, this finding indicates nontransferability between daytime and nighttime crash. Possible reason is that concrete road is normally built for urban area with dense traffic and lower speed limit compared to rural area; therefore, crashes on such road are prone to less severe crash. On the other hand, the shift in effect during nighttime crashes may be due to self-selectivity of urban riders and nighttime environment such as trip purposes (travelling to/from entertainment center etc.,), speed selection (higher speed due to less vehicles on the road), traffic volume and visual condition.

Indicator for crash on curve road was statistically significant in only 2016 daytime, with the effect increasing the likelihood of fatal injury (**Table 5.7**). Indicator for crash on road on grad was statistically significant in 2018 and 2019 daytime, and 2016 and 2017 nighttime model, with their consistent and stable effect increasing the likelihood of fatal injury (**Table 5.7-5.8**). This may be attributed to the increased difficulties in controlling the motorcycle at such locations (Chang et al., 2021). Previous studies (Alnawmasi and Mannering, 2019; Chang et al., 2016; M. Islam, 2021; S. Islam and Brown, 2017; X. Li et al., 2021; Se et al., 2022b; Xin et al., 2017) also confirmed these findings.

Regarding the intersection types, indicator for crashes at the 4-leg intersection was significant in only the 2018 daytime model, with the effect increasing the probability of fatal injury (**Table 5.7**). However, indicator for crashes at 3-intersection was found increasing the probability of fatal injury and minor injury significantly in 2018 nighttime and 2019 daytime, respectively, thus indicating that nighttime conditions pose a higher risk of fatal injury relative to daytime. Although without mention the time-of-day, some research (Tamakloe et al., 2022; Vajari et al., 2020) found that intersection related crashes increased possibility of higher injury severity; whereas, other (Chang et al., 2016; Geedipally et al., 2011; S. Islam and Brown, 2017; Savolainen and Mannering, 2007) found otherwise. Whereas, some study found intersection-related crashes have heterogenous effect on motorcyclist injury severity level (Se et al., 2021a; Se et al., 2022b).

As shown in **Table 5.7-5.8**, indicator for crashes at within U-turn area was significant in the 2016 daytime/nighttime and 2019 daytime models, with the consistent effect increasing the likelihood of fatal injury (note: it also affected the means of random parameter in the 2019 nighttime crash model; see section below). Reasonable explanation is that riders' exposure to dangerous conflicts such as cross- and weaving conflicts encourage dangerous crash types such as angle or right-angle collision with oncoming traffic.

Indicator for crashes on the bridge was significant in 2018 daytime and 2017 nighttime, with the consistent effect increasing the probability of fatal injury. Again, previous work also confirmed this finding (Se et al., 2021a).

Compared to rural crashes, indicator for urban road crashes was significant in all 2016-2019 daytime models and 2017-2019 nighttime models, with the stable and consistent marginal effect decreasing the likelihood of fatal injury (**Table 5.7-5.8**). It should be also noted that urban road indicator produced random parameters in the 2017 daytime and 2019 nighttime model, with the majority of the observations increasing the likelihood of minor injury (see **Figure 5.4g** and **Figure 5.5l**). This may be attributed to the possibility that urban areas have lower speed limits and higher traffic volume that restrict automobiles to operate at lower speed, compared to rural areas. This finding is in line with numerous previous work (Kashani et al., 2014; X. Li et al., 2021; Se et al., 2021a; M. S. Shaheed and Gkritza, 2014; M. S. B. Shaheed et al., 2013; Vajari et al., 2020; Zambon and Hasselberg, 2006).

5.7.3 Environmental characteristics

Indicator for crashes on wets road was found statistically significant nighttime crash in all periods from 2016-2019 with a stable and strikingly high effect increasing the probability of fatal injury (**Table 5.8**). This finding indicates that riding a motorcycle during nighttime on wet road surfaces is significantly more dangerous than that of daytime time. Without considering time-of-day, several existing literatures (Quddus et al., 2002; Savolainen and Mannering, 2007; Se et al., 2021a; Se et al., 2022b) also confirmed the finding.

Indicator for crashes under rainy conditions was significant in only 2018 daytime (with the effect increasing likelihood of fatal injury), in 2018 and 2019 nighttime with the average effect decreasing the probability of fatal injury (**Table 5.7-5.8**). Also, raining indicator produced random parameter in the 2019 nighttime model with 39.84% of the observations increasing likelihood of fatal injury (**Figure 5.5m**). Reasonable explanation could be that rainy weather plus nighttime conditions could act as a disincentive against any risk-seeking behaviors that may encourage risk of higher injury severity level (e.g., speeding, aggressive driving, dangerous overtaking, etc.). Previous studies (Ijaz et al., 2021; X. Li et al., 2021; Se et al., 2021a; Se et al., 2022b; Vajari et al., 2020) also confirm this finding.

Compared to normal weekdays, indicator for crashes during the weekends was statistically significant in all daytime and nighttime periods from 2016-

2019, with the consistent and stable effect increasing the probability of fatal injury (**Table 5.7-5.8**). Again, this finding may be attributed to the difference between the self-selectively of nature of daytime and nighttime riders. Although time-of-day was not reported, existing literature also confirmed the finding that motorcycle crashes on weekend are prone to more severe crash (Cunto and Ferreira, 2017; M. Islam, 2021; Jung et al., 2013; M. S. Shaheed and Gkritza, 2014; Xin et al., 2017).

Compared to crashes during nighttime on lit road, indicator for crashes on unlit roads was significant in all nighttime periods from 2016-2019, with the stable effect increasing the likelihood of fatal injury (**Table 5.8**). This finding is fairly logical and supported by previous literatures (Alnawmasi and Mannering, 2019; Chang et al., 2016; M. Islam, 2021; Jou et al., 2012; Savolainen and Mannering, 2007; Se et al., 2022b; M. S. Shaheed and Gkritza, 2014; Xin et al., 2017).

5.7.4 Crash characteristics

Compared to hitting larger vehicles, indicator for riders hitting other motorcycle was found statistically significant in all daytime and nighttime models from 2016-2019, with the consistent and stable effect increasing the likelihood of minor injury severity. Similarly, compared to hitting larger vehicles type, indicator for rider hitting passenger vehicle were also found to increase the probability of minor injury in 2017-2019 nighttime crashes. Indicator for rider hitting the pickup truck was significant in 2016-2018 daytime and nighttime models which, in general, their marginal effect increasing the probability of fatal injury. It should be noted that hitting pickup truck indicator produced random parameter in 2017 daytime (39.2% of the observation increased the likelihood of fatal injury **Figure 5.4h**) and 2016-2018 nighttime model (with majority of the observations increased the probability of fatal injury; see **Figure 5.5b**, **Figure 5.5e** and **Figure 5.5h**). Indicator for rider hitting van/minibus had higher probability of sustaining fatal injury in 2016-2018 daytime and 2018-2019 nighttime model (it produced random parameter in 2018 nighttime; see **Figure 5.5i**). Compared to hitting smaller vehicles, indicator for riders hitting a truck was significant in all daytime and nighttime from 2016-2019, with the consistent and stable effect increasing the likelihood of fatal injury (strikingly high). Note that, hitting-truck indicator also produced random parameters in 2016 daytime and 2019 nighttime with majority of the such crash observations increasing the likelihood of fatal injury (see **Figure 5.4b** and **Figure 5.5n**, respectively). These findings can be supported by reasonable explanations that the impact of collision with larger-sized vehicles could produce high impact collision forces that subsequently increase the probability of higher injury severity level. Another intuitive explanation is that riders may be more likely to hit the unforgiving object such as a sharp of the larger vehicle corner (especially, pickup-truck and large truck) or motorcyclists' bodies are more directly exposed to potential injury without the energy-dissipating structure and safety features (Alnawmasi and Mannering, 2019). This finding is in line with past studies (Chang et al., 2016; Ijaz et al., 2021; J. Li et al., 2021; Rifaat et al., 2012; M. S. B. Shaheed et al., 2013; Waseem et al., 2019).

Compared to head-on crashes, indicator for rear-end crash type was significant in 2016 daytime, 2018 daytime and 2019 nighttime, with their effect increasing the likelihood of minor injury (**Table 5.7-5.8**). Similarly, indicator for sideswipe crashes was significant in all models 2016-2019 daytime and nighttime (except 2017 nighttime), with stable and consistent marginal effects increasing the likelihood of minor injury (**Table 5.7-5.8**). Note that sideswipe crash also produced random parameters in 2016 daytime, 2018 daytime and 2018 nighttime, with a minority proportion of observations increasing likelihood of fatal injury (see their distributional split in **Figure 5.4c**, **Figure 5.4k** and **Figure 5.5j**, respectively). Possible explanations are that 1) these crash type are more likely to occur at the intersection area, where motorcyclists are forced to operate at lower speed and tend to more carefully ride at or near intersection as they adjust for greater perceived risk; and 2) less transfer of energy in a same-direction crash (Geedipally et al., 2011; Savolainen and Mannering, 2007). This finding is also in line with the past research (Jung et al., 2013; X. Li et al., 2021; Se et al., 2021a). Compared to head-on crashes, indicator for single-motorcycle crashes was significant in 2016 daytime, 2018 daytime and 2019 daytime and nighttime, with their effects increasing likelihood of minor injury (**Table 5.7-5.8**). The single-motorcycle crash indicator also produced random parameter in 2019 daytime, with 24.81% of such crash observations increasing the likelihood of fatal injury. This may be attributed to the possibility that some single-vehicle crash involved hitting fixed-object such as trees and poles (Geedipally et al., 2011; Savolainen and Mannering, 2007).

Lastly, indicator for head-on crash type was significant in 2017-2019 daytime (note: it produced random parameter in 2018 daytime, see **Figure 5.4l**) and 2016-2019 nighttime, with the effect, in general, increasing the likelihoods of fatal injury (**Table 5.7-5.8**). Reasonable explanation may be due to extremely high crash impact due to opposite direction collision. Existing literature also agree with this finding (Chang et al., 2021; Jung et al., 2013; X. Li et al., 2021; Schneider and Savolainen, 2011; Se et al., 2022a).

5.7.5 Heterogeneity in means and variances

Some important finding from heterogeneity in mean include (**Table 5.5-5.6**): 2016 daytime model: crash on flush median road increase the mean of hitting large truck, thereby increasing the probability of fatal injury; 2017 daytime model: male rider and alcohol indicator decrease the mean of pillion indicator, rendering fatal injury less likely, and alcohol indicator increase the means of crash on depressed median road, making fatal injury more likely; 2018 daytime model: crash on 2 lane road increase the mean of speeding crash and side-swipe crash, making fatal injury more likely, and crash on 4 lane road also increase the mean of side-swipe crash, rendering fatal injury more likely; 2019 daytime model: crash on depressed median increase the mean of work zone crash, thereby making fatal injury more likely; 2016 nighttime model: hitting-crossing-object crash increase the mean of crash on 4 lane road and hitting-a-pickup truck crash, making fatal injury more likely; 2017 nighttime model: alcohol and crash on median road indicator increase the mean of crash on frontage lane, making fatal injury more likely; 2018 nighttime model, curve road indicator increase the mean of hitting a pickup truck, making fatal injury more likely; 2019 nighttime model: crash with U-turn area increase the mean of crash during rain, making fatal injury more likely.

Findings regarding heterogeneity in variance include (**Table 5.5-5.6**): 2017 daytime model: crash on main lane road decrease variation of speeding and urban road crashes, and increase variation of hitting a pickup truck; 2018 daytime model: crash on wet road increase variation of speeding crash, hit-crossing-object crash and side-swipe crash; 2019 daytime model: speeding crash increase the variation of work zone and single-motorcycle crashes; 2016 nighttime model: rear-end crash increase variation of 4 lane crash; 2017 nighttime model: speeding crash decrease variation of depressed median crash and increase variation of hitting pickup truck crash; 2018 nighttime model: crash on depressed median road increase variation of the crash on concrete road and side-swipe crash and decrease variation of hitting pickup truck crash; 2019 nighttime model: crash on frontage lane decrease the variation of speeding crash, and alcohol indicator increase variation of crash during rain and decrease variation of urban road crash.

5.8 Conclusions and Policy Recommendations

Using motorcycle crashes data in Thailand for 2016-2019, this paper studied the difference between factors affecting motorcyclist injury severity at daytime and nighttime and investigated how the effects of these factors have changed over the consider time period, by estimating mixed ordered probit approach that allows the influence of crash-level attributes on means and variance of the unobserved factors (or random parameters). Three injury-severities levels were considered in model estimation: minor-, severe-, and fatal injury.

Although majority of the factors showed uniform effects across yearly and time-of-day models (still varied in marginal effect magnitudes), the model result of this study has clearly shown that some factors influencing motorcyclist injury severity probabilities not only are temporally unstable, but also nontransferable between daytime and nighttime crashes. Various riders, roadway, environmental, and crash characteristics were found statistically significant in affecting the probabilities of motorcyclist's crash severity in yearly models and time-of-day models. In addition, some notable factors had heterogenous effect on the resulting motorcyclist injury severities including presence of pillion, exceeding speed limit, work zone, raised median, depressed median, concrete road, urban road, hitting pickup truck, sideswipe crash, and single-motorcycle crash. The models' finding and likelihood ration tests clearly confirmed the nontransferability (between daytime and nighttime) and temporal instability (from one year to the next). Interpretation of these factors provided more insight into motorcycle safety, which can be of value to decision/policy maker, traffic management departments and roadway designers seeking to promote highway safety targeted motorcycle road users.

The possibility of temporal instability has profound implications for current safety practice and allocation of funds for safety improvements. In terms of practical implications, this study selects the important findings and discuss possible policy recommendations, which are discussed below:

a) Male motorcyclists had a higher probability of sustaining fatal injury in the nighttime crash (particularly the latest period─2018 and 2019). Therefore, nighttime male riders should be mainly targeted when providing the motorcycle safety awareness campaign.

b) With stable effect across the four years period (2016-2019), riders with the presence of pillion had higher risk of being killed in the crash, regardless of time-of-day. Exceeding the speed limit crash also strongly influenced the motorcyclist injury severity (more serious in nighttime crashes). More efforts should be made to encourage helmet use and riders to operate the motorcycle at safety speed, particularly when there is pillion. Strict law enforcement such as heavy fines or temporary banning the driving license should be implemented on exceeding the speed limit. Repeat offences should also receive higher penalties. Modern technology should also be used to monitor, evaluate, and punish the riders more effectively to strengthen traffic law enforcement. For example, there should be a national demerit point system and information linking system between the traffic police and the Department of Land Transport which has a driving license database.

c) With stable effect across yearly daytime crashes (2016-2018), riders illegally overtaking other vehicle types had a strikingly high probability of sustaining fatal injury. More effort should be made to the motorcycle riding training program on safety riding and dangerous interaction with other vehicles operating on the road (such as safe lane changing and safe distance to overtake).

d) With stable effect across yearly nighttime crashes, riders with fatigue had higher risk of being killed in the crash. With strikingly high probability, nighttime riders should be targeted to ensure that riders should not use motorcycles if they are under fatigue conditions. This can be done through a safety awareness campaign.

e) With stable effect across yearly daytime and nighttime crashes, motorcycle-crashes on frontage lanes were less likely to result in fatality. Option to build a frontage lane to local or community traffic should be considered in the future road construction project.

f) Work zone crashes were more likely to result in fatality, in the latest nighttime and daytime periods. More effort by the road safety inspectors/auditors should be made to ensure that the work zone provides a sufficient safety environment particularly for vulnerable road users. For example, ensure that the corresponding companies should provide direction lighting systems on the detours, guardrails, sufficient reflective material, clean road surface etc.

g) Crashes on 2 lane roads, crashes on depressed/flush median road and crashes on rural road (compared to urban road) were more likely to result in fatality. Since depressed/flush median road and 2 lane road are common for rural areas, more effort should be made to increase safety awareness of rural riders such as operating at safe speed and wearing helmets (more particularly when operating on 2 lane roads at nighttime). Consider increasing the public transport systems for rural areas in order to reduce the number of motorcycle users.

h) Crashes on raised median road and crashes on concrete road were less likely to result in fatality during daytime, but more likely to result in fatality during nighttime. This is due to the difference in nature of riders between daytime and nighttime urban riders. More effort should be made to increase strict implementation of traffic regulation during nighttime in urban areas on riding over the speed limit, not wearing a helmet, and riding under intoxication.

i) Crashes on curve roads and road on grade increased the probability of fatal injury in daytime and nighttime periods. More effort to enforce the speed limits regulation should be increased at such locations.

j) Intersection-related motorcycle crashes had lower probability of fatal injury in daytime, but higher risk of resulting in fatality in nighttime. With stable effects across the two-year period (2016 and 2019) in both daytime and nighttime, crashes at the U-turn had a higher probability of fatal injury. More effort should be made to ensure sufficient visibility, sufficient sight distance, intersection/U-turn sign board and speed limit board, and increase driver awareness of motorcycle riders particularly at urban intersection areas and how to safely use the U-turn via various safety awareness campaigns.

k) With stable effect across all yearly nighttime models, crashes on wet roads had a higher probability of fatal injury. More efforts should be made to increase safety awareness of motorcyclists, particularly after raining during nighttime.

l) With stable effect across all yearly daytime and nighttime models, weekend crashes were more likely to result in fatality, compared to weekday crashes. More efforts should be made to increase helmet use, alcohol awareness (especially at nighttime), and enforcement of zero-tolerance laws for motorcycle riders on speeding, under the influence of alcohol and violation of traffic regulation, particularly on the weekends.

m) With stable effect across all yearly nighttime models, crashes on unlit road were more likely to result in fatality, compared to lit road. More efforts should be made to increase the nighttime visibility on roadway segments, particularly small communities in rural areas.

n) Motorcycle crashes involving hitting large vehicle types (pickup truck, van, mini bus, and large truck) were found to increase the likelihoods of fatal injury in various yearly daytime and nighttime models. More efforts should be made to increase riders' awareness when riding on roads with mixed traffic. Provision of exclusive motorcycle lanes should be considered to avoid interaction with other vehicle types on the roadway segment. The government should consider introducing separate or restricted motorcycle lanes in future urban planning.

o) With stable and strikingly high effect across all yearly daytime and nighttime models, head-on crashes were more likely to result in fatality. More efforts should be made to increase effectiveness of motorcyclist training program and encourage riders to wear helmet, keep safe braking distance and avoid speeding/overtaking (especially on the wind roads or blind curve) that potentially reduce the relative force that can result from the frontal impact and minimize the risk of going out of control and crossing the centerline.

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CHAPTER VI

CONCLUSIONS

Road Traffic Crashes (RTC) remain a top global public health crisis causing an unacceptable number of avoidable mortalities and disabilities. As a consequence, Road Traffic Injuries (RTI) bring extra burden upon the health systems and economy of the countries, loss of human resources, and untold or unseen misery and economic consequences to families who have to deal with bereavement or disabled relatives. Among these deaths and injuries, nearly 90% occur in low- and middle-income countries (LMIC). The risk of road traffic death is more than three times higher in low- and middle-income countries (an average of 27.5 per 100,000 population) than high-income countries (an average of 8.3 per 100,000 population). As a middle-income and developing country, Thailand encounters tremendous economic and emotional burdens due to road accidents with a death rate of 32.8 per 100,000 population. These situations entail in-depth research concerning the resulting injury severities of crashes, which also requires further investigation to provide insightful knowledge for developing appropriate and targeted strategies for crash mitigation and prevention. The current dissertation comprehensively investigates factors impacting driver-injury severities in single-vehicle crashes (the crash type with highest frequency rate) and motorcyclist-injury severities in motorcycle-related crashes (the crash type with highest mortality rate) in the context of Thailand.

To effectively generate the most accurate and reliable results, crash-injury severity research needs to fully address two issues: possible temporal shift of explanatory factors and possible unobserved heterogeneity underlying the crash data. Recognizing these necessities, the current dissertation contributes towards addressing the computational challenges in crash-injury severity analysis by considering temporal influences and analysing risk factors effecting driver- and motorcyclist-injury severity utilizing the advanced econometric approaches to account for unobserved heterogeneity. **The first objective of the dissertation** contributes to safety literature by empirically investigating the temporal stability of factors influencing driver-injury severities in single-vehicle crashes using an advanced heterogeneity model (i.e., a correlated random parameters approach with heterogeneity in means and variances). **The second objective of the dissertation** comprehensively explores the possible differences between speeding driving-related crash and non-speeding driving crashes on the outcomes of driver-injury severity by carefully accounting for possible temporal shift and unobserved heterogeneity. **The third objective of the dissertation,** with a primary focus on motorcyclist injury policy evaluation, conducts an in-depth examination on the differences between weekday, weekend, and holiday motorcyclist injury severity alongside a temporal instability investigation while also accounting for unobserved heterogeneity, and run series of out-of-sample prediction simulations to better understand the difference between time-of-year and yearly motorcyclist-injury severity probabilities. Lastly, **the fourth objective of the dissertation** contributes to motorcyclist safety by uncovering possible time-of-day variation and temporal shift on resulting motorcyclist injury severities, and provides insight into motorcyclist safety through policy recommendations.

The proposed contributions are organized along four parts. The rest of the chapter is organized as follows. Section 6.1 through 6.4 discusses the substantive contributions of the dissertation for each objective examined in the dissertation. Section 6.5 summarizes and concludes the contributions of the dissertation. Lastly, Section 6.6 discusses the limitations of the dissertation and direction for future research.

6.1 Summary of the first objective

In this particular objective, the study fills the gaps of literature as follow: 1) Investigates possible temporal instability of risk factors affecting driver-injury severity of single-vehicle run-off-road crashes, utilizing the crash data from middle-income developing country of Southeast Asia—Thailand, 2) Compares and contrast between two advanced econometric modeling (Uncorrelated random parameters model with heterogeneity in means and variance versus Correlated random parameters model with heterogeneity in means). Several groups of factors are considered in the analysis including driver characteristics, roadway attributes, vehicle characteristics, crash characteristics, environmental and temporal characteristics, and spatial characteristics.

Two series of likelihood ratio tests results clearly indicate substantial temporal instability in the model specifications and estimated parameters across 2011 through 2017. Although some factors generate stable effects across some periods, their marginal effect values clearly vary across the time periods. In sum, those variables with stable effects are: seatbelt use, alcohol consumption, raised median, depressed median, barrier medians, passenger cars, pick-up trucks, and large trucks, running-off-road on straight, running-off-road on straight and hit a guardrail, and hitting road island; and variables with unstable effects are: male drivers, speeding, asphalt pavement, weekends, and crashes on weekends during nighttime on lit road. The observed temporal instability and variability may be attributed to the improvements in the safety features of vehicles, driver adaptation to such changes in technology, changes in police reporting practice in recording crash data, safety education campaign efforts and law enforcement overtime.

Comparing between the two methodological approaches, a model accounting for heterogeneity in variance is found to outperform a model accounting for correlation among random parameters. However, both models offer their own unique result. That is, if allowing heterogeneity in variances is selected, potential findings of the correlation between unobserved characteristics would be ignored; and if allowing correlation among random parameters is selected, insightful findings from allowing heterogeneity in the variance of random parameter would be neglected. To sum up, trade-off between model fit, prediction accuracy, and explanatory power should be carefully considered in the future study in terms of how fit it would be to the research objective.

6.2 Summary of the second objective

In this particular objective, the study fills the gaps of literature by comparing between the driver-injury severity associated with speeding driving-related and non-speeding driving-related crashes while also accounting for possible temporal shift and unobserved heterogeneity (using random parameters binary logit with heterogeneity in mean and variance). Multiple groups of factors are considered in the modeling including driver characteristics, roadway attributes, vehicle characteristics, crash characteristics, environmental and temporal characteristics, and spatial characteristics.

The transferability tests show a significant difference between driver-injury severity of crashes involving speeding and non-speeding driving, whereas, temporal stability tests indicate that both speeding and non-speeding driving crash injury severity models exhibits substantial temporal instability over the three considered periods (i.e., 2012–2013, 2014–2015, and 2016–2017).

Key findings in speeding crash models are: variables with lower probability of severe/fatal injury: restrained driver, van, passenger car, pickup truck, running off road on straight and hitting guardrail and mounting traffic island; whereas variables with higher probability of severe/fatal injury central, eastern, and southern parts of the country.

Key findings in non-speeding driving crash models are: variables with lower probability of severe/fatal injury: restrained driver, truck, and running off road on straight and hitting guardrail; whereas variables with lower probability of severe/fatal injury: driver under influence of alcohol and van. Contradicting findings between the two crash types are: older driver, male driver, raised median, two-lane and four-lane roads, road under construction, U-turn, van, raining, unlit and lit roads, and morning peak hour.

Using the findings from this particular objective of the dissertation, recommendations could be as follows: 1) Young drivers, male drivers and drivers associated with alcohol consumption should be firmly targeted with strict law enforcement and emphasized when conducting safety education campaigns. 2) Effort encouraging the use of seatbelt through educational campaigns and a suitable penalty on drivers who don’t equip seatbelt should be continually implemented (since this indicator is significant in both crash types models, with the stable effect decreasing injury severity level). 3) In urban areas (especially nighttime), controlling the safe speed should be effectively implemented through increasing police checkpoints and speed cameras (from findings of crashes on raised and barrier median roads). 4) Related authorities should regularly audit the quality of the minibus and van (of the private transportation companies) in terms of safety aspect and penalize the stakeholders who still operate using unsafe minibuses and vans. 5) Highways designers should consider provision of guardrail protection for all curve road sections and run-off-roadway accident prone areas (since variables reflecting crashes hitting guardrail are significant in both crash types models, with the stable effect decreasing injury severity level).

The results of this objective highlight the importance of modelling the crash severity by considering speeding crashes and non-speeding crashes separately, and the importance of temporal instability with unobserved effects in determinants that affect driver-injury severities.

6.3 Summary of the third objective

In this particular objective, the study fills the gaps of literature by taking different perspectives from the previous motorcycle crash-injury severity studies as follow: 1) Comprehensively examines the differences between weekday, weekend, and holiday motorcyclist injury severities. 2) Fully accounts for possible temporal influences and unobserved heterogeneities. 3) Extensively conducts a series of out-of-sample prediction simulations to better understand the changes in motorcyclist injury severity distributions across time-of-year and yearly models. Several groups of factors are considered in the modeling including rider characteristics and actions, roadway attributes, environmental and temporal characteristics, and crash types and characteristics.

Two series of likelihood ratio tests strongly reject the null hypothesis that the model estimates between weekday, weekend, and holiday crashes are transferable in all years from 2016 to 2019, and that influential factors are temporally stable over the considered period in all time-of-year crashes.

While majority of the variables have different effects on weekday, weekend, and holiday motorcyclist-injury severity, some variables have unified effect across all time-of-year crash as follows: variables with higher probability of severe and fatal injuries are riding with a pillion, four lanes, two lanes, curves, grades, intersections, lit roads, unlit roads, midnight/early morning, hitting pickup/van/bus/truck, and head-on crashes; and variables with higher probability of minor injury are hitting motorcycles and urban areas). With respect to temporal influence, stable factors in the weekday model are hitting-motorcycle and urban indicators, hitting-truck and midnight/early morning. Stable factors in the weekend model are four-lane roads, two-lane roads, hitting motorcycles, and hitting trucks. Stable factors in the holiday model are riding with a pillion and hitting passenger cars. It should be noted that numerous variables are also found significant in only three year-models with temporal stability including unlit roads, midnight/early morning, evening, hitting vans, hitting trucks, and head-on crashes, with their effects increasing the likelihood of fatal injury.

Two series of out-of-sample prediction simulations are conducted. The results also additionally confirm the temporal instability and nontransferability between the effects of weekday, weekend, and holiday crashes on motorcyclist injury severity distribution. Number of possible factors may play roles in these observed instability including variability in trip purposes, traffic volumes, traffic compositions, human attitudes/behaviors/activities/cultures, policy implementations, varying in riding experiences, new technologies and other advancements introduced to motorcycles, macroeconomic conditions, and changes of rider attitudes and behaviors as a response to the changes of other road users due to the evolution of vehicle technologies, other social media platforms and various safety education campaigns, and self-selective nature of the motorcyclists.

The results of this objective highlight the importance of accounting for day-of-week and holiday transferability and temporal instability with unobserved effects in determinants that affect motorcyclist injury severity. The findings of this objective of the dissertation may provide valuable knowledge for practitioners, researchers, institutions, and decision-makers to enhance highway safety, specifically motorcyclist safety, and facilitate the development of more effective motorcycle crash injury mitigation policies.

6.4 Summary of fourth objective

In this particular objective, the study fills the gaps of literature by seeking answers to the following questions: 1) What are the contributing factors to motorcyclist injury severities of crashes on highways? 2) What contributing factors have heterogeneous effects on resulting motorcyclist injury severities? 3) What are the differences in the impact degree of factors between the daytime and nighttime motorcycle crashes? 4) Are the effects of risk factors impacting motorcyclist injury severities of the daytime and nighttime motorcycle crashes temporally stable? Wide ranges of factors are considered in the modeling including rider characteristics and actions, roadway attributes, environmental and temporal characteristics, and crash types and characteristics.

Even though numerous factors generate unified effects across yearly and time-of-day models (still varied in marginal effect magnitudes), the likelihood ratio tests and the modeling results of indicate that some factors influencing motorcyclist injury severity probabilities not only are temporally unstable, but also nontransferable between daytime and nighttime crashes. Some notable factors are found to have heterogenous effects on the resulting motorcyclist injury severities including riding with pillion, speeding, work zone, raised median, depressed median, concrete road, urban road, hitting pickup truck, sideswipe crash, and single-motorcycle crash. Interpretation of these factors provided more insight into motorcycle safety, which can be of value to decision/policy makers, traffic management departments and roadway designers seeking to promote highway safety targeted motorcycle road users.

6.5 Contribution of the Dissertation

This dissertation contributes substantially towards application of advanced heterogeneity modeling approaches and comprehensive understanding of the contributing factors of driver-injury severities in single-vehicle crashes and motorcyclist-injury severities in the context of a middle-developing country, Thailand, along two major directions: 1) empirically extending the application of the advanced econometric modeling approach including uncorrelated random parameters logit with heterogeneity in means and variances, correlated random parameters with heterogeneity in means, and uncorrelated random parameters ordered probit with heterogeneity in means and variances; 2) comprehensively considering the temporal shift of contributing factors of driver-injury severities in single-vehicle crashes, driver-injury severities in speeding and non-speeding driving crashes (also considering transferability assessment), motorcyclist-injury severities in weekday crashes, weekend crashes, and holidays crashes (also considering transferability assessment), and motorcyclist-injury severities in nighttime crashes and daytime crashes (also considering transferability assessment).

The dissertation also makes a substantial empirical contribution to the existing safety literature. The observed temporal instability and nontransferability (between subsets) have profound implications for current safety practices and allocation of funds for safety improvements and can be used to devise safety-conscious decision support tools to facilitate proactive approach in assessing medium and long-term policy-based countermeasures.

6.6 Limitations and Future Direction

Like any research, this dissertation is not without limitations. First: conducting the crash-injury severity analysis without considering the effect of weather conditions may possibly produce bias results. That is, drivers tend to intuitively adapt their behavior and abilities relative to weather conditions when operating their vehicles. This issue potentially makes interpreting and comparing crash data analysis between adverse and fine weather conditions laborious and challenging (Theofilatos and Yannis, 2014). It would be fruitful for future work to consider crash-injury severity modeling under adverse weather conditions separately, while also accounting for temporal shift. Second: the findings of the fourth objective of the dissertation clearly show that the urban riders may change their behavior significantly from daytime to nighttime. This may suggest the need to separately consider crash-injury severity models by location (urban versus rural) and by time-of-day while also considering temporal stability assessment. Third: numerous important crash-level characteristics are not available in this dissertation including controlled/uncontrolled intersections/junctions, vehicle direction, stop signs, give-way signs, markings, pre-crash maneuvers by vehicles and motorcycles, motorcycle’s right of way violation, shoulder width, lane number, availability of footpath shoulders, and at-fault or not-at-fault etc. It would be fruitful for future work to attempt to collect a more comprehensive dataset and address these limitations while also considering possible temporal instability.

6.7 References

Theofilatos, A., and Yannis, G. (2014). A review of the effect of traffic and weather characteristics on road safety. **Accident Analysis and Prevention**, 72, 244-256.

APPENDIX I

LIST OF PUBLICATIONS

List of Publications

Se, C., Champahom, T., Jomnonkwao, S., Karoonsoontawong, A., and Ratanavaraha, V. (2021). Temporal stability of factors influencing driver-injury severities in single-vehicle crashes: A correlated random parameters with heterogeneity in means and variances approach. **Analytic Methods in Accident Research**, 32, 100179.

Se, C., Champahom, T., Jomnonkwao, S., Kronprasert, N., and Ratanavaraha, V. (2022). The impact of weekday, weekend, and holiday crashes on motorcyclist injury severities: accounting for temporal influence with unobserved effect and insight from out-of-sample prediction, **Analytic Methods in Accident Research**, 36, 100240.

Se, C., Champahom, T., Jomnonkwao, S., Karoonsoontawon, A., and Ratanavaraha, V. (2022). Analysis of driver-injury severity: a comparison between speeding and non-speeding driving crash accounting for temporal and unobserved effects. **International Journal of Injury Control and Safety Promotion**, 1-14.

Se, C., Champahom, T., Jomnonkwao, S., and Ratanavaraha, V. (2022). Fatal motorcycle crashes analysis in Thailand: Accounting for unobserved heterogeneity. **Australasian Road Safety Conference 2022 (ARSC 2022) 28th–30th September**, Ōtautahi Christchurch, New Zealand.

BIOGRAPHY

Dr. Chamroeun Se was born in January 17, 1994 at Battambang Province, Cambodia. He initially completed his primary school education at O-Nhor Primary School, secondary school education at Sovann Kiri Secondary School, and completed high school at Phnom Thom High School. He then further obtained Bachelor’s Degree in Civil Engineering at Paragon International University (former Zaman University) and Master’s degree in Transportation Engineering at Suranaree University of Technology.

Dr. Chamroeun Se researched and wrote articles focusing on highway safety using econometric and statistical models with an emphasis on injury severity analysis of run-off-roadway crashes (roadway departures), single-vehicle crashes and motorcycle crashes. He has published papers in multiple international journals including, **Analytic Methods in Accident Research**, **Accident Analysis & Prevention**, **International Journal of Injury Control and Safety Promotion**, **Process Safety and Environmental Protection**, and **Behavioral Sciences**. His current research focusses on application of advanced Statistical and Econometric Methods and Temporal Instability Analysis for crash-injury severity research.