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Study on Motorcycle Safety in Negotiation with Horizontal Curves in Florida and Development of Crash Modification Factors

Task 3: Crash Analysis and Development of CMFs

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Table of Contents

Table of Contents ..... **ii**
List of Figures ..... **iii**
List of Tables ..... **iv**
Chapter 1 Introduction **5**
Chapter 2 Methodologies **7**
2.1 Considerations in Motorcycle Crash Analysis 7
2.2 Statistical Methodology for Crash-Frequency Data: Mixed-effects Negative Binomial Model 8
2.3 Statistical Methodology for Crash-Severity Data: Mixed-effects Logistic Model 9
2.4 Case-Control Methodology for Crash Modification Factor Development 10
Chapter 3 Analysis for Motorcycle Crash-Frequency **13**
3.1 Descriptive Statistics of Motorcycle Crash-Frequency Data 13
3.2 Estimated Mixed-Effects Negative Binomial Model 14
3.3 Model Interpretation 15
3.3.1 Curve Radius and Type 15
3.3.2 Curve Length 16
3.3.3 Geometric Characteristics 16
3.3.4 Pavement Characteristics 17
3.3.5 Traffic Characteristics 17
3.4 Crash Modification Function for Horizontal Curvature 17
Chapter 4 Analysis for Motorcycle Crash-Severity **19**
4.1 Descriptive Statistics of Motorcycle Crash-Severity Data 19
4.2 Estimated Mixed-Effects Logistic Model 20
4.3 Model Interpretation 21
4.3.1 Curve Parameters 21
4.3.2 Speed 22
4.3.3 Roadway Characteristics 23
4.3.4 Pavement 23
4.3.5 Environment 24
4.3.6 Crash Characteristics 25
4.3.7 Rider Characteristics 25
Chapter 5 Crash Modification Factors Development using Case-Control Method **27**
5.1 Data Collection and Descriptive Statistics 27
5.2 Model Estimation 28
5.3 CMF for Curve Radius 29
Chapter 6 Summary and Conclusions **30**

List of Figures

Figure 1 – Overall Procedure for Data Collection and Processing 6
Figure 2 - Power vs. Control/Case Quotient 11
Figure 3 - Types of Horizontal Curves 14
Figure 4 - Expected Motorcycle Crash Frequency by Curve Radius and Curve Type 16
Figure 5 - Crash Modification Function by Curve Radius 18
Figure 6 - Predicted Probability of Severe Injuries by Curve Radius and Curve Type 22
Figure 7 - Predicted Probability of Severe Injury by Lighting Condition 24
Figure 8 - Procedure for Case-Control Data Collection 27
Figure 9 - Crash Modification Factors of Horizontal Curve Radius for Motorcycle Crash on Rural Two-Lane Highways 29

List of Tables

Table 1 - Tabulation for Simple Case-Control Analysis 11
Table 2 - Descriptive Statistics of Motorcycle Crash-Frequency Data 13
Table 3 - Estimated Mixed-Effects Negative Binomial Model 14
Table 4 - Descriptive Statistics of Single-Motorcycle Crash-Severity Data 19
Table 5 - Fitted Mixed-Effects Logistic Model with Average Marginal Effects 20
Table 6 - Descriptive Statistics of Risk Factors for Case-Control Study 28
Table 7 - Matched Case-Control Model for Motorcycle Crashes on Rural Two-lane Highways 28
Table 8 - Risk Factors of Motorcycle Crashes on Rural Two-Lane Curve Segments 30

Chapter 1
Introduction

Task 3 investigated the motorcycle crash pattern on horizontal curves on Florida rural roads. Through the crash analyses, the research team expected to archive the following goals:

- Quantify the effects of horizontal curvature on motorcycle crash occurrence and severity.
- Identify factors contributing to motorcycle crash frequency on rural horizontal curves in Florida.
- Identify factors contributing to motorcycle crash severity on rural horizontal curves in Florida.
- Develop Crash Modification Factors/Functions (CMF) for motorcycle crashes on rural horizontal curves.

The systematic crash analysis was fully based on the historical crash data collected in Task 2. Two crash data types were used to address motorcycle safety issues on horizontal curves from two aspects: how horizontal curvature and other factors influence motorcycle crash occurrence (based on frequency data), and how horizontal curvature and other factors influence the severity in a motorcycle crash (based on severity data).

- *Motorcycle crash frequency*, indicating the likelihood of motorcycle crashes, is defined as the number of motorcycle crashes occurring within a given period (e.g., one year), on a roadway entity (e.g., a horizontal curve). Multiple crashes occurring at the same location over a period may be an indication of a safety issue and should be investigated and addressed appropriately.
- *Motorcycle crash severity* represents the outcome of a motorcycle crash—that is, given that a motorcycle crash occurred, the most severe injury level involved in the crash. In the Florida Crash Analysis and Reporting (CAR) system, five crash severity levels are defined: Fatal, Incapacitating-Injury, Non-Incapacitating Injury, Possible Injury, and No Injury. The high probability of severe injuries from motorcycle crashes may imply serious safety issues and more attention in safety improvement.

To address the safety effects of a geometric design (e.g., horizontal curvature) or a countermeasure (e.g., speed advisory sign), statistical comparison between the geometric design/countermeasure and a baseline (without the geometric design/countermeasure) is the basic method to distinguish the difference in crash frequency/severity from the baseline. The data organizations for the statistical comparisons typically can be classified as either before-after or cross-sectional. A before-after study surveys the change of crash frequency and/or severity before and after implementation of a treatment (design or countermeasure) at the same sites. A cross-sectional study compares the difference of crash frequency or severity over different sites during the same period. This study adopted the cross-sectional design for the following reasons:

- Horizontal curvature is a constant factor. Very few curve sites in which horizontal curvature varied over time were found within the observation period (2005–2015). Thus, before-after design is not feasible for assessing horizontal curvature.
- In current FDOT databases (e.g., Roadway Characteristics Inventory), it is difficult to capture treatments that may influence motorcycle safety and vary over the observation period (e.g., speed control signs). For these factors, before-after design also is not feasible.
- A cross-sectional study can provide enough samples over space within the observation period to capture the difference of horizontal curvature and other factors in motorcycle safety.

A cross-sectional study has some issues that should be addressed, as described in Chapter 2.

The research team implemented a procedure for crash analysis, as shown in Figure 1. The following chapters describe the details and results of each step in the procedure.

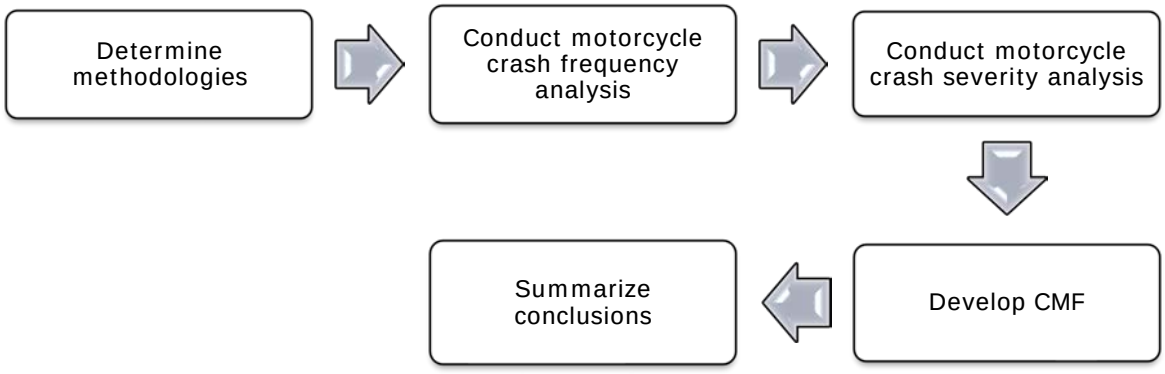

Figure 1 – Overall Procedure for Data Collection and Processing

Chapter 2
Methodologies

This chapter presents the efforts to determine crash analysis methodologies, including considerations in motorcycle crash analysis, statistical technologies for crash frequency and severity modeling, and methodologies for CMF development.

2.1 Considerations in Motorcycle Crash Analysis

Traffic crashes are stochastic events. Thus, statistical methodologies are a natural choice for analyzing crash data. Various statistical methodologies, such as descriptive analysis, hypothesis testing, regression model, etc., have been used widely in crash analysis. In this study, regression models were used to fit crash-frequency and crash-severity data since they can quantify the relationships between the dependent variable (crash frequency or crash severity) and explanatory variables (horizontal curvatures, geometric design, pavement conditions, rider characteristics, etc.).

Motorcycle crash data, either frequency or severity, have specific characteristics and considerations in crash modeling:

- *Unobserved heterogeneity* – The occurrence and severity of a motorcycle crash is a complicated outcome that involves complex interactions among human factors and roadway characteristics, vehicle features, traffic attributes, and environmental conditions [1]. Sample data for crash modeling usually are retrieved from police accident reports and roadway characteristics inventory files; it is impossible to include all factors influencing the occurrence of a traffic crash in these databases over time, space, and individuals. The unobserved factors, correlated with the observed variables, potentially can cause the issue of unobserved heterogeneity—that is, differences among crash observations that are not measured. To obtain enough samples, this study collected motorcycle crash data over a long period (2005–2015, 11 years). Many factors might change significantly over this period and could not be captured due to the lack of detailed information, e.g., the variation of friction number and rider characteristics over the time.

  Ignoring the issue of unobserved heterogeneity may lead to biased and inconsistent parameter estimation, erroneous inferences, and predictions [1].

- *Confounding variables* – A confounding variable is an extraneous variable that correlates with both the dependent variable and the independent variable. Ignoring confounding variables in crash modeling, it may obtain a bias inference on the cause and degree of the change of motorcycle crashes. For example, traffic volume is a typical confounding variable related to both crash frequency (high traffic volume means a high probability of crash occurrence) and horizontal curvature (high traffic volume is more likely to occur on a high-class roadway with better geometric design, such as small curve radius). Without controlling confounding variables (match or average), the crash reduction on a curve may be caused by low traffic exposure rather than improvement of geometric design.

- *Self-selectivity/endogeneity* – The values of some factors are dependent on crash occurrence and severity. An example of this issue is that speed warning signs are more likely placed on curves with high number of and/or severe crashes. This issue is called self-selectivity or endogeneity. If this endogeneity is ignored, an erroneous conclusion may be derived [2]. In the example, a wrong conclusion that speed warning signs tend to increase motorcycle crash frequency or severity may be obtained if we do not consider that the sites with speed warning controls are more likely to have high crash numbers or severe crash severity.
- *Low sample-mean and excess zero observations* – Motorcycle crashes are rare and random events. Some roadway entities may have few observed motorcycle crashes (low sample-mean and excess zeros) due to low motorcycle exposure. In this study, more than 98% of curves sites have zero observations of motorcycle crashes for the 11 years (2005–2015) of the study; the sample-mean is 0.02 crashes per 11 years. With the low sample mean and excess zeros, the traditional methodology may cause incorrect estimation and erroneous inferences [2].
- *Risk compensation* – Rider characteristics/behaviors are the most direct factors causing a motorcycle crash. Rider behaviors responding to a change of roadway conditions in negotiation of horizontal curves are first determined by his/her understanding on the change of roadway conditions. If a rider realizes the roadway conditions are dangerous, he/she may take some safer behaviors (e.g., low speed, pay more attention on surrounding environment, etc.). If a rider feels safe, he/she may tend to take risk behaviors (e.g., high speed, careless riding, etc.), which may result in motorcycle crashes or increasing the crash severity. Ignoring this issue, the effects of a treatment may be over- or under-estimated [3].

This study addressed these issues from different aspects: good design of data collection scheme, proper modeling technologies, and careful interpretation. Mixed-effects models potentially can capture unobserved heterogeneity by allowing parameters to vary across observations [3]. These models also potentially can give insight into other issues, such as risk compensation and endogeneity. In this study, two mixed-effects models (mixed-effects negative binomial model and mixed-effects logistic model) were used for fit crash-frequency and crash-severity data, respectively, to address unobserved heterogeneity and risk compensation. The case-control method was also used to develop CMF by controlling confounding variables and addressing low-mean sample.

2.2 Statistical Methodology for Crash-Frequency Data: Mixed-effects Negative Binomial Model

Motorcycle crash frequency, as an indicator of the likelihood of motorcycle crash occurrence, is usually measured as a count variable with over-dispersion (variance greater than mean). The Negative Binomial regression model is an extension of the Poisson model to overcome possible over-dispersion in the crash data [2], [3]. In a Poisson regression model, the probability of curve segment *i* having y_i crashes per a given period is shown as:

$$P(y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!} \qquad (1)$$

where P (y_i) is the probability of curve segment *i* having y_i crashes per a given period and λ_i is the Poisson parameter for curve segment *i,* which is equal to curve segment *i's* expected number of crashes per a given period, E[y_i]. Poisson regression models can be estimated by specifying the Poisson parameter λ_i as a function of explanatory variables by typically using a log-linear function:

$$\lambda_i = EXP(\beta X_i) \qquad (2)$$

where X_i is a vector of explanatory variables and β is the vector of regression coefficients [4]. To address this over-dispersion problem, the Negative Binomial model can be derived as

$$\lambda_i = EXP(\beta X_i + \varepsilon_i) \qquad (3)$$

where EXP(ε_i) is a gamma-distributed error term with mean 1 and variance α. The addition of this term allows the variance to differ from the mean as VAR[y_i] = E[y_i][1 + αE[y_i]] = E[y_i] + αE[y_i]^2. The negative binomial probability density function can be described as

$$P(y_i) = \left(\frac{1/\alpha}{(1/\alpha)+\lambda_i}\right)^{1/\alpha} \frac{\Gamma[(1/\alpha)+y_i]}{\Gamma(1/\alpha)y_i!}\left(\frac{\lambda_i}{(1/\alpha)+\lambda_i}\right)^{n_i} \qquad (4)$$

where Γ(·) is a gamma function.

To resolve the issue of unobserved heterogeneity, a random-parameters (mixed-effects) negative binomial regression model was developed to allow some parameters to vary across crash observations rather than fixed in traditional models. The equation of regression coefficients for random parameters model is given as

$$\beta_i = \beta + \varphi_i \qquad (5)$$

where φ_i is a randomly distributed term with mean 0 and variance σ^2. With this, the log-likelihood function can be shown as

$$LL(\beta) = \sum_{\forall i} \ln \int_{\varphi_i} f(\varphi_i) P(y_i \mid \varphi_i) d\varphi_i \qquad (6)$$

where *f*(·) is the probability function of the φ_i. Since Equation 6 cannot be derived to a closed form, the simulated maximum likelihood approach with a Halton sequence was used to estimate the model parameters [5].

2.3 Statistical Methodology for Crash-Severity Data: Mixed-effects Logistic Model

Motorcycle crash-severity, indicating the outcome of a motorcycle crash, is a categorical variable. In this study, the crash-severity data were aggregated into a binary variable: 1 -fatality or severe injury, and 0 - slight injury or no injury. Thus, binary choice models, such as logistic model was naturally used to fit the crash-severity data. The logistic model, also named the binary logit model, is expressed as [6]:

$$\Pr(y_i = 1 \mid X_i) = \Phi(X_i\beta) = \frac{\exp(X_i\beta)}{1+\exp(X_i\beta)} \qquad (7)$$

where Pr(·) denotes the probability of the injury severity (y_i) of crash observation i; β is the vector of regression coefficients; X_i is the vector of explanatory variables for crash observation i; and Φ is the cumulative distribution function (CDF) of the logistic distribution.

To resolve the issue of unobserved heterogeneity, mixed-effects models (also referred as random parameters models) were developed to allow some parameters to vary across crash observations, rather than fixed in traditional models. The equation of mixed-effects logistic model is given as

$$\Pr(y_i = 1 \mid X_i) = \int \Phi(X_i\beta) \cdot f(\beta \mid \varphi) d\beta = \int \left(\frac{\exp(X_i\beta)}{1+\exp(X_i\beta)} \right) \cdot f(\beta \mid \varphi) d\beta \qquad (8)$$

where $f(\beta \mid \varphi)$ is the density function of random parameter β with distribution parameter φ. Eq. 8 is a mix of two distributions: $\Phi(X_i\beta)$ for error item and $f(\beta \mid \varphi)$ for random parameters. The log-likelihood function for the random parameter logistic model can be derived as

$$LL(\beta) = \sum_i \{ y_i \ln(\Pr(y_i = 1 \mid X_i) + (1 - y_i) \ln(1 - \Pr(y_i = 1 \mid X_i)\} \qquad (9)$$

Since Eq. 9 cannot be derived to a closed form, the simulated maximum likelihood approach with a Halton sequence was used to estimate the model parameters [5].

2.4 Case-Control Methodology for Crash Modification Factor Development

As described in FHWA's *A Guide to Developing Quality Crash Modification Factors*, more recently, the case-control method has been employed to estimate CMFs for geometric design elements [7]. Case-control studies are based on cross-sectional data. However, unlike cross-sectional studies that select samples base the presence and absence of a specific characteristics (e.g., horizontal curve), case-control studies select samples based on outcome status (e.g., crash or no crash) and then determine the risk factor (e.g., sharp curve) within each outcome group. In case-control studies, cases are defined as those roadway entities that experience at least one crash during the observation period, and the corresponding controls are drawn from those entities that do not experience a crash during the period. A matching scheme, which randomly matches cases with controls that are similar in some potential confounding variables, provides a balanced design and automatically adjusts the estimates for the effects of variables included in the matching scheme.

The ratio of controls to cases may vary and often depends on the availability of time, budget, and other factors. As the ratio of controls to cases increases, the power of the design increases but at a decreasing rate (Figure 2).

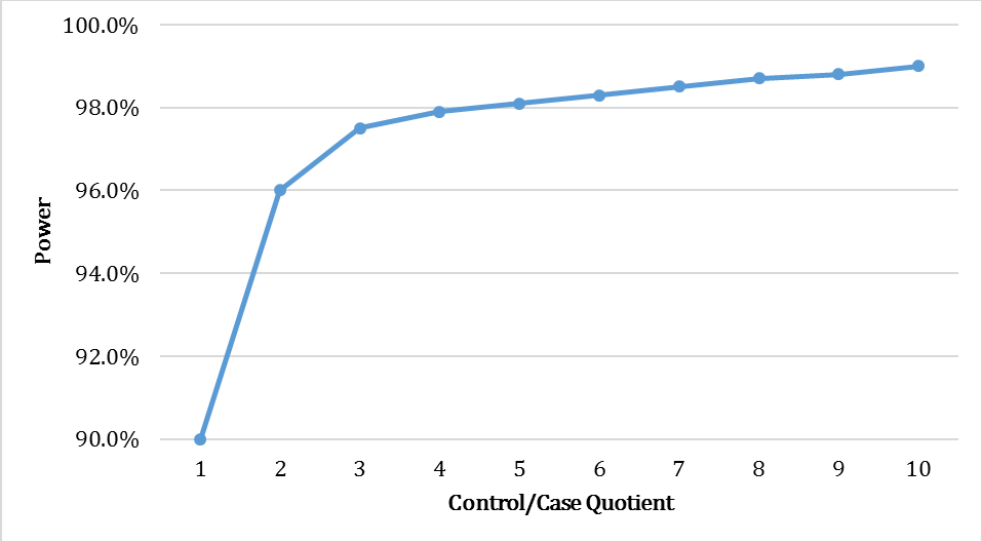

Figure 2 – Power vs. Control/Case Quotient

Case-control studies assess whether exposure to a potential treatment (e.g., a sharp curve) is disproportionately distributed between the cases and controls, thereby indicating the likelihood of an actual benefit/loss from the treatment [7]. A simple case-control analysis is shown in Table 1.

Table 1 – Tabulation for Simple Case-Control Analysis

Risk Factor	Number of Cases	Number of Controls
With	A	B
Without	C	D

The odds ratio (CMF), indicating the relative risk, is expressed as the expected increase or decrease in the outcome in question due to the presence of the risk factor. An odds ratio greater than 1.0 suggests that the presence of the treatment increases risk, while a value less than 1.0 would suggest a decrease in risk. Using the notation in Table 1, the odds ratio is calculated as

$$\text{Odds Ratio} = \text{CMF} = \frac{A/B}{C/D} = \frac{AD}{BC} \tag{10}$$

The case-control method may be very useful for studying rare events, such as motorcycle crash-frequency data with low mean and excess zeros, because the number of cases and controls is predetermined. Another advantage of the case-control design is that multiple treatments may be investigated in relation to a single outcome using the same sample.

In this study, a complex case-control method was implemented. A conditional logit model was used to estimate the odds ratio. The conditional probability of an outcome associated with the unmatched variables (the risk factor in which we are interested) $X_1, X_2, \ldots, X_m$ for each member of the i^{th} matched set is given by

$$P(Y = 1) = 1/\{1 + exp[-(\alpha_i + \sum_{j=1}^{m} \beta_j X_j)]\} \tag{11}$$

where:

m – number of explanatory variables

α_i – effect of matching variables for each matched set

β_j – estimated regression parameters for unmatched explanatory variables

X_j – unmatched explanatory variables included in the model

The odds ratio (CMF) for the unmatched explanatory variable β_j can be calculated as

$$Odd\ Ratio = Exp(\beta_j) \quad (12)$$

Chapter 3
Analysis for Motorcycle Crash-Frequency

3.1 Descriptive Statistics of Motorcycle Crash-Frequency Data

The motorcycle crash-frequency data were organized at the site level, which means one record in the dataset represents one roadway entity (horizontal curve). In total, 2,179 horizontal curves (sites) were identified from the FDOT RCI database with the following characteristics: rural roads, two lanes, and paved median only. Information on geometry, traffic, and pavement data was extracted from the RCI database for each identified curve. In total, 439 motorcycle crashes for 11 years (2005–2015) were spatially matched to the identified horizontal curves. The descriptive statistics of the collected data are shown in Table 2.

Table 2 – Descriptive Statistics of Motorcycle Crash-Frequency Data

Variable Description	Mean	Std. Dev	Min.	Max.
Dependent variable: number of motorcycle crashes (2005–2015)	0.198	0.581	0	8
Curve characteristics				
Logarithm value of curve radius (in log[ft])	8.239	0.969	4.54	13.44
Reverse curve indicator (1 if curve is in reverse curves, 0 otherwise)	0.190	0.393	0	1
Curve length (in mi)	0.350	0.225	0.08	6.07
Geometric characteristics				
Shoulder width (in ft)	11.928	2.766	2	24
Auxiliary lane indicator (1 if auxiliary lane exists in curve segment, 0 otherwise)	0.024	0.153	0	1
Grade indicator (1 if vertical grade is present, 0 otherwise)	0.114	0.318	0	1
Access density: number of junctions per mile	3.026	4.731	0	48
Pavement characteristics				
Average pavement condition (scale 0–5)	3.798	0.420	2.4	5.0
Pavement roughness indicator (1 if 11-year average international roughness index (IRI) is greater than 75 in./mi, 0 otherwise)	0.309	0.462	0	1
Traffic characteristics				
Average annual daily traffic (AADT) (in 000 of vehicles/day)	4.269	2.959	0.46	25.18

The types of horizontal curve are classified as reverse curve and non-reverse curve. A reverse curve consists of two jointed simple curves, but curving in opposite directions. A non-reverse curve could be a simple curve or a compound curve (a series of two or more simple curves with deflections in the same direction immediately adjacent to each other). The types of horizontal curves are shown in Figure 2.

1 – Single Curve 2 – Compound Curve 3 – Reverse Curve

Figure 3 - Types of Horizontal Curves

3.2 Estimated Mixed-Effects Negative Binomial Model

The software package NLOGIT 5 was used to the Mixed-effects Negative Binomial model. The estimated random parameters negative binomial regression logistic model, along with average marginal effects, is presented in Table 3.

Table 3 – Estimated Mixed-Effects Negative Binomial Model

Variable Description	Estimated Parameter	*t-Statistic*	Marginal Effect
Constant	-2.771	-3.78	
Curve characteristics			
Logarithm value of curve radius (in log [ft])	-0.208	-3.29	-0.027
Standard deviation of parameter distribution	(0.047)	(6.42)	
Reverse curve indicator (1 if curve is reverse curve, 0 otherwise)	-0.490	-2.61	-0.064
Standard deviation of parameter distribution	(0.734)	(4.78)	
Curve length (in mi)	1.067	4.98	0.138
Geometric characteristics			
Auxiliary lane indicator (1 if auxiliary lane is present in curve segment, 0 otherwise)	0.777	2.59	0.101
Grade indicator (1 if vertical grade is present, 0 otherwise)	0.409	2.40	0.053
Access density: number of junctions per mile	0.061	5.10	0.008
Pavement characteristics			
11-year average pavement condition (scale 0–5)	0.318	2.38	0.041
Standard deviation of parameter distribution	(0.034)	(2.21)	
Pavement roughness indicator (1 if 11-year avg international roughness index (IRI) greater than 75 in./mi, 0 otherwise)	0.007	0.05	0.001
Standard deviation of parameter distribution	(0.507)	(4.86)	
Traffic characteristics			
Average annual daily traffic (AADT) (in 000 vehicles per day)	0.165	8.93	0.021
Overdispersion parameter α	0.745	5.29	
Number of observations			2179
Log-likelihood with constant only			-1249.37
Log-likelihood at convergence			-1068.38
McFadden pseudo R-squared (ρ^2)		0.145	

3.3 Model Interpretation

3.3.1 Curve Radius and Type

The logarithm value of the curve radius is a random parameter that is normally distributed, with a mean of -0.208 and standard deviation of 0.047. This indicates that increasing the curve radius nearly always decrease the motorcycle crash frequency (less than 0.05% of the distribution would have a positive value) but with varying magnitude across the population of rural two-lane roadway segments. The increase of curve radius can reduce the risk factors for motorcyclists in negotiation with curves, such as speed variation, poor sight distance, and complexity of negotiation maneuvers.

The reverse curve indicator produced a normally-distributed negative parameter with a mean of -0.490 and a standard deviation of 0.734, suggesting that for 74.8% of roadway segments, the presence of reverse curve tends to result in a decrease in crash occurrences. For the remaining roadway segments, the presence of reverse curve tends to result in an increase in crash occurrences. This is perhaps because a great portion of motorcycle riders (around 74.8%) would become more alert and take safety compensation behaviors (e.g., slow speed) to compensate for the difficulty of negotiating reverse curves. Other riders still suffer the risk caused by reverse curve, such as frequent adjustments of riding posture, poor sight distance, etc.

Figure 3 presents the expected motorcycle crash frequency (per 11 years) by curve radius and type, holding other factors at average over sample observations. The relationship between motorcycle crash frequency and curve radius is near-logarithmic. The expected motorcycle crash frequency decreases rapidly with an increase in radius if the curve is sharp (radius < 1,500 ft). When the radius exceeds 1,500 ft but is less than 3,000 ft, the decrease slope is smaller than sharp curves but still higher than a flat curve (radius > 4,000 ft). It is also obvious that the presence of reverse curve can significantly decrease the motorcycle crash frequency at each radius level.

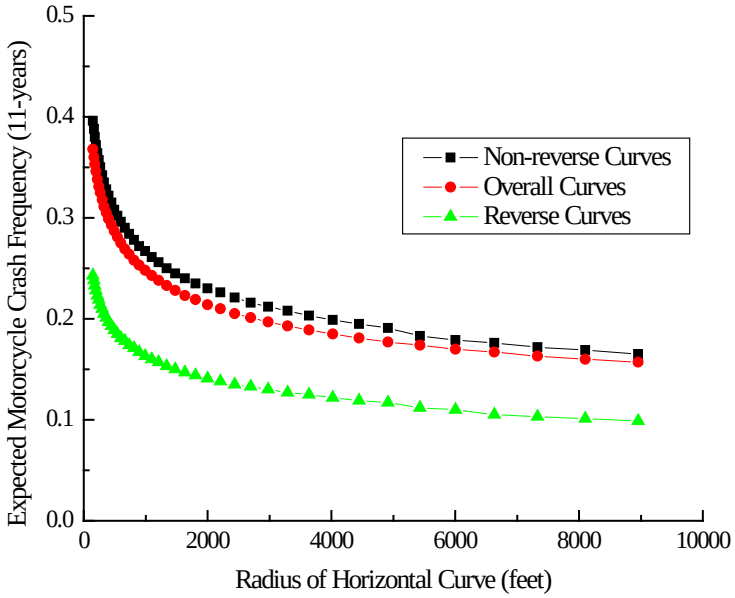

Figure 4 – Expected Motorcycle Crash Frequency by Curve Radius and Curve Type

3.3.2 Curve Length

Since some factors (e.g., shoulder width) may vary with the increase in curve length, curve length could not be treated as an exposure variable that be assumed to have a linear relationship with expected crash frequency. The model shows that the length of horizontal curve is a positive fixed parameter, which indicates that the average number of motorcycle crashes increases with an increase in curve length because motorcycle riders would gain more exposure time with increase of curve length. The marginal effects showed that a one-mile increase in curve length on RTU roads results in an average increase of 0.138 motorcycle crashes per 11 years.

3.3.3 Geometric Characteristics

Auxiliary lanes, linking access points and, consequently, increased potential traffic conflicts, were found to increase the probability of motorcycle crash occurrence on horizontal curves. Marginal effects show that the presence of auxiliary lanes would increase the average number of motorcycle crashes on RTU roads by 0.101 (per 11 years).

The vertical grade variable produced a positive fixed parameter that increases the motorcycle crash frequency by 0.053 crashes per 11 years. The interaction between horizontal curves and vertical slope can significantly decrease the sight distance and increase the complexity of riding maneuvers.

The number of access points per mile on horizontal curves is a positive fixed parameter, since high access density may increase traffic conflicts. Marginal effects show that each additional junction per mile can result in an increase of 0.008 motorcycle crashes per 11 years on RTU roads.

3.3.4 Pavement Characteristics

Pavement condition variable ranges from 0 (completely deteriorated) to 5 (excellent pavement condition). This variable produced a normally-distributed negative parameter with a mean of 0.318 and a standard deviation of 0.034, suggesting that for nearly all rural two-lane curves, the number of motorcycle crashes increases when the pavement conditions become better. This finding seems counterintuitive and could be related to a variety of unobserved factors. One possible unobserved factor is related to motorcyclist risk compensation behavior; that is, motorcycle riders who believe pavement quality is good tend to take risky behaviors, such as higher speed and less alertness. On the other hand, if riders feel unsafe with poor pavement conditions, they may take low-risk behaviors (e.g., low speed, more attention on surrounding environment). Similar findings about the effects of good pavement condition tending to increase vehicle crash frequency were found in several previous studies [8], [9].

Another measure of pavement condition is the International Roughness Index (IRI), which measures roughness of road surface. In Florida, the IRI is measured in inches per mile, with lower values indicating a smoother surface. The model shows that a rough-pavement (IRI > 75 in./mi) is a random positive parameter, with a mean of 0.007 and a standard deviation of 0.507, suggesting that 50.6% of riders tend to increase motorcycle crash frequency horizontal curves with rough pavement and 49.4% of them tend to decrease motorcycle crash frequency.

3.3.5 Traffic Characteristics

Annual average daily traffic (AADT) results in a positive fixed parameter, indicating that a growth of 1,000 vehicles per day increases the expected number of motorcycle crashes by 0.021 per 11 years.

3.4 Crash Modification Function for Horizontal Curvature

The crash modification function (CMF) for horizontal curve radius is a mathematical function that describes the impacts of the curve radius on motorcycle crash frequency relative to a baseline. Assuming that the curve radius of 5,000 ft is the baseline, the crash modification function can be derived as

$$CMF = \frac{\lambda(R_i \mid X)}{\lambda(R_0 \mid X)} = \frac{EXP(-0.208 \times LN(R_i) + \overline{\beta}\,\overline{X})}{EXP(-0.208 \times LN(R_0) + \overline{\beta}\,\overline{X})} = \left(\frac{R_i}{5000}\right)^{-0.208} \qquad (13)$$

where $\lambda(R_i \mid X)$ is the expected number of crashes along curve segments with radius R_i; R_0 is 5,000 ft, the baseline of CMF; -0.208 is the estimated parameter of radius in Table 2; $\overline{X}$ represents the vector of the other variables; and $\overline{\beta}$ is the vector of estimated parameters for the other variables.

The curve of the CMF for horizontal curve radius is shown in Figure 4. The CMF curve has a similar nonlinear tendency with the curve of curve radius—expected motorcycle crash frequency. The safety performance in reducing motorcycle crashes is more significant in the low range of curve radius (radius < 2,000 ft). For example, the expected motorcycle crash frequencies for horizontal curves of 150, 500, and 1000 ft are 2.07, 1.61, and 1.40 times,

respectively, as many as the frequency for the radius 5,000 ft. In other words, if decreasing the radius from 5,000 ft to 150 ft, 500 ft, and 1,000 ft, the expected motorcycle crash frequency will increase by 107%, 61%, and 40%, respectively. If increase the radius from 5,000 ft to 6,000 ft, the percent of expected motorcycle crash frequency is only decreasing by 4%.

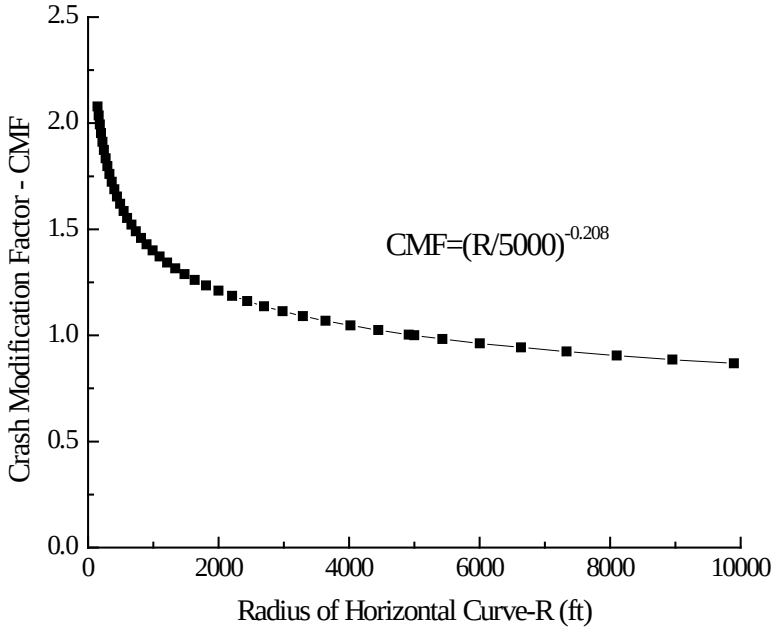

Figure 5 – Crash Modification Function by Curve Radius

The crash modification factor for reverse curve indicates the relative change of expected motorcycle crash frequency comparing reverse curves with non-reverse curves (simple or compound curves).

$$CMF = \frac{\lambda(\text{Re}\,verse \mid X)}{\lambda(Non-reverse \mid X)} = \frac{EXP(-0.490\times 1+\overline{\beta}\overline{X})}{EXP(-0.490\times 0+\overline{\beta}\overline{X})} = EXP(-0.490) \approx 0.61 \qquad (14)$$

where $\lambda(\text{Re}\,verse \mid X)$ is the expected number of crashes along reverse curves; $\lambda(Non-reverse \mid X)$ is the expected number of crashes along non-reverse curves; -0.490 is the estimated parameter of reverse curve in Table 2; $\overline{X}$ represents the vector of the other variables; and $\overline{\beta}$ is the vector of estimated parameters for the other variables. The crash modification factor of curve type indicates that the number of motorcycle crashes would decrease 39% (=1 - 0.61) when a reverse curve is present on a rural two-lane road.

Chapter 4
Analysis for Motorcycle Crash-Severity

4.1 Descriptive Statistics of Motorcycle Crash-Severity Data

Motorcycle crash-severity data were organized at crash-level, which means one record in the dataset represents one crash. In this study, only single-motorcycle crashes were considered to exclude the influence from other vehicles. In addition, the sample size of single-motorcycle crashes on rural two-lane curves is too small (219) to conduct a meaningful statistical analysis. Thus, this study identified 8,597 horizontal curves on both urban and rural roads. In total, 2,168 single-motorcycle crashes occurred between 2005 and 2015 and were spatially matched to the identified horizontal curves. The descriptive statistics of the collected data are shown in Table 4.

Table 4 – Descriptive Statistics of Single-Motorcycle Crash-Severity Data

Variable Description	Mean	Std. Dev
Crash severity (1 if crash severity is fatality or incapacitating injury, 0 otherwise)	0.385	0.487
Sharp curve indicator (1 if radius of curvature is less than 1500 ft, 0 otherwise)	0.260	0.439
Moderate curve indicator (1 if radius of curvature is 1500–4000 ft, 0 otherwise)	0.377	0.485
S-curve indicator (1 if curve type is composite curve with different offset directions, 0 otherwise)	0.293	0.455
High motorcycle speed indicator (1 if motorcycle speed is more than 50 mph, 0 otherwise)	0.466	0.499
Speeding indicator (1 if motorcycle crash cause is exceeding speed limit, 0 otherwise)	0.065	0.246
Speed control sign indicator (1 if traffic control facility is speed control sign, 0 otherwise)	0.313	0.464
Auxiliary lane indicator (1 if auxiliary lane exists in crash location, 0 otherwise)	0.371	0.483
Vegetation median indicator (1 if median type is vegetation, 0 otherwise)	0.360	0.480
Paved median indicator (1 if median type is paved median, 0 otherwise)	0.827	0.378
Road access control indicator (1 if road access is full or partial control, 0 otherwise)	0.321	0.467
Poor pavement condition indicator (1 if pavement condition index is less than 3, 0 otherwise)	0.025	0.156
Roughness indicator (1 if pavement roughness index is more than 80 in./mi, 0 otherwise)	0.370	0.483
Friction indicator (1 if skid test number is larger than 40, 0 otherwise)	0.330	0.470
Dry road surface indicator (1 if road surface condition is dry, 0 otherwise)	0.883	0.321
Darkness indicator (1 if light condition is darkness without street light, 0 otherwise)	0.144	0.351
Darkness with street light indicator (1 if light condition is darkness with street light, 0 otherwise)	0.233	0.423
Tree indicator (1 if motorcycle hit tree or shrubbery, 0 otherwise)	0.012	0.111
Barrier wall indicator (1 if motorcycle hit utility concrete barrier wall, 0 otherwise)	0.041	0.197
Other-fixed object collision indicator (1 if collision with other fixed objects, 0 otherwise)	0.117	0.322
Alcohol/drugs indicator (1 if motorcycle crash is under influence of alcohol/drugs, 0 otherwise)	0.100	0.300

Helmet indicator (1 if all motorcycle occupants wear safety helmet, 0 otherwise)	0.630	0.483
Proper driving indicator (1 if crash cause is no improper driving or action, 0 otherwise)	0.239	0.427
Weekend indicator (1 if motorcycle riding is on Saturday or Sunday, 0 otherwise)	0.429	0.495
Younger motorcycle rider indicator (1 if motorcycle rider age is under 30, 0 otherwise)	0.351	0.477
Older motorcycle rider indicator (1 if motorcycle rider age is over 60 old, 0 otherwise)	0.097	0.296
Male indicator (1 if motorcycle rider is male, 0 otherwise)	0.919	0.273

4.2 Estimated Mixed-Effects Logistic Model

The software package NLOGIT 5 was used to estimate the mixed-effects logistic model. The estimated mixed-effects logistic model, along with marginal effects (ME), is presented Table 5.

Table 5 – Fitted Mixed-Effects Logistic Model with Average Marginal Effects

(All random parameters are normally distributed with standard deviation in parentheses)

Variable Description	Estimated Parameter	*t*-statistic	ME (%)
Constant	-1.784	-6.83	
Sharp curve indicator (1 if radius of curvature is less than 1500 ft, 0 otherwise)	0.269	2.09	6.08
Moderate curve indicator (1 if radius of curvature is 1500–4000 ft, 0 otherwise)	0.070 (0.763)	0.65 (7.08)	1.58
S-curve indicator (1 if curve type is a composite curve with different offset directions, 0 otherwise)	0.258 (0.729)	2.50 (6.01)	5.82
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mph, 0 otherwise)	1.068	9.91	24.11
Speeding indicator (1 if motorcycle crash cause is exceeding speed limit, 0 otherwise)	0.743	3.81	16.78
Speed control sign indicator (1 if traffic control facility is speed control sign, 0 otherwise)	0.351	3.58	7.93
Auxiliary lane indicator (1 if auxiliary lane exists in crash location, 0 otherwise)	-0.200	-2.09	-4.51
Vegetation median indicator (1 if median type is vegetation, 0 otherwise)	0.220	2.06	4.98
Paved median indicator (1 if median type is paved median, 0 otherwise)	0.326	2.35	7.36
Road access control indicator (1 if road access is full or partial control, 0 otherwise)	-0.596	-4.96	-13.47
Poor pavement condition indicator (1 if pavement condition index is less than 3 (poor), 0 otherwise)	-0.546	-1.75	-12.34
Roughness indicator (1 if pavement roughness index is more than 80 in./mi, 0 otherwise)	-0.205	-2.00	-4.64
Friction indicator (1 if skid test number is larger than 45, 0 otherwise)	0.322	3.22	7.28
Dry road surface indicator (1 if road surface condition is dry, 0 otherwise)	0.506	3.48	11.42
Darkness indicator (1 if light condition is darkness without street light, 0 otherwise)	0.368	2.78	8.32
Darkness with street light indicator (1 if light condition is darkness with street light, 0 otherwise)	0.260	2.20	5.88
Tree indicator (1 if motorcycle hit tree or shrubbery, 0 otherwise)	0.692	1.72	15.62

Barrier wall indicator (1 if motorcycle hit utility concrete barrier wall, 0 otherwise)	0.915	4.06	20.66
Other-fixed object collision indicator (1 if collision with other fixed object, 0 otherwise)	0.333	2.29	7.51
Alcohol/drugs indicator (1 if motorcycle crash is under the influence of alcohol/drugs, 0 otherwise)	0.319	2.01	7.20
Helmet indicator (1 if all motorcycle occupants wear safety helmet, 0 otherwise)	-0.370	-3.83	-8.35
Proper driving indicator (1 if crash cause is no improper driving or action, 0 otherwise)	-0.527	-4.66	-11.90
Weekend indicator (1 if motorcycle riding is on Saturday or Sunday, 0 otherwise)	0.217	2.38	4.91
Younger motorcycle rider indicator (1 if motorcycle rider age is under 30, 0 otherwise)	-0.221	-2.17	-5.00
Older motorcycle rider indicator (1 if motorcycle rider's age is over 60, 0 otherwise)	0.721 (1.382)	4.44 (6.09)	16.27
Male indicator (1 if motorcycle rider is male, 0 otherwise)	-0.206 (2.390)	-1.36 (21.24)	-4.66
Model statistics			
Number of observations	2168		
Restricted log likelihood	-1445.03		
Log-likelihood at convergence	-1315.16		
McFadden pseudo R-squared (ρ^2)	0.086		

4.3 Model Interpretation

4.3.1 Curve Parameters

Sharp curves (radius < 1500 ft), as a fixed parameter, are more likely to increase the probability of severe injuries in single-motorcycle crashes by 6.08%, compared to non-sharp curves (radius ≥ 1500 ft). Small radii greatly decrease negotiation space and increase the complexity of riding maneuvers. Consequently, injury-deteriorating riding behaviors (e.g., excessive speed, erroneous lean angle, flawed trajectory) on sharp curves are exceedingly significant with s small curve radius.

Moderate curves (1500 ft ≤ radius < 4000 ft) have random effects on single-motorcycle injury severities, following a normal distribution, with a mean of 0.07 and a standard deviation of 0.763. To further address the random effects, another mixed-effects logistic model was developed to exclude the disturbance of sharp curves that were included in the modeling baseline (moderate curve indicator = 0); all sharp curve crashes were rejected from the sample. Results showed that the indicator of moderate curves is still a random parameter (mean = 0.0876; SD = 0.1957; *t*-statistic for mean = 0.92, and SD = 2.16). It could be inferred that the heterogeneity of unobserved factors related to moderate curves (e.g., rider safety intentions, complexity of curve negotiation, traffic/environmental/ geometric features) is a reason for the random effect. Because the positive effect (increasing injury severity) is close to the negative effect (decreasing injury severity), the overall effect of moderate curves is insignificant (*t*-statistic for mean = 0.65, Table 4). Evidence is that there is no significant difference between the probability of a negative coefficient and a positive coefficient (46.3% vs. 53.7%).

The reverse curve (S-curve) indicator is another normally-distributed random parameter, with a mean of 0.258 and a standard deviation of 0.729. Motorcycle riders traveling on a

reverse curve (Figure 2) must continuously change counterweight directions for tracking the change of curve offsets. These frequent adjustments of riding posture are likely to cause loss of control and, consequently, result in 63.8% of single-motorcycle crashes being more likely to cause severe injuries on reverse curves. On the other hand, reverse curves may cause safety compensation behaviors (e.g., slow speed if rider feels unsafe) to compensate for the risk of severe injuries on reverse curves for the remaining 36.2% of single-motorcycle crashes. On average, reverse curves tend to increase the probability of severe injury by 5.82%.

As shown in Figure 5, the probability of severe injuries in single-motorcycle crashes is a deceasing function (piecewise) of curve radius by different curve types. Compared to flat curves, sharp curves increase the probability of severe injuries in single-motorcycle crashes by 7.7% (=41.1% - 33.4%) overall and 7.3% (= 41.5% -34.2%) for reverse curves.

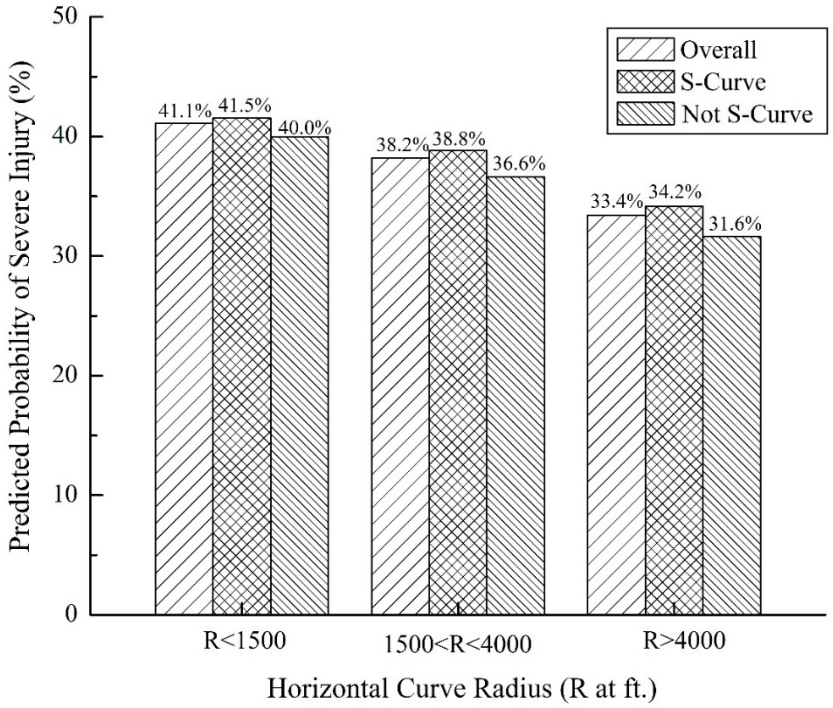

Figure 6 - Predicted Probability of Severe Injuries by Curve Radius and Curve Type

4.3.2 Speed

Speed is the most predominant factor contributing to injury severity. Damage to motorcycle occupants is related to pressure, deceleration, change in velocity, and kinetic energy dissipation to human bodies; all these factors are the increasing function of speed [10]. The marginal effect of the high-speed indicator (> 50 mph) denotes that high speed is likely to increase the probability of severe injuries by 24.11%.

Speeding is another dangerous factor that tends to increase the probability of severe injuries by 16.78%. These findings are consistent with previous studies [11]–[18].

Based on the model, speed control signs are more likely to increase the probability of severe injury in crashes on curves. This counterintuitive effect is caused by the issue of self-selected sample (endogeneity): speed control signs are more likely to be installed in zones in which high-speed issues have existed and significant crashes occurred. An analysis of the sample data indicated that the average speed in single-motorcycle crashes with speed control signs (53.7 mph) is significantly higher than the average speed without speed control signs (47.8 mph).

4.3.3 Roadway Characteristics

The presence of auxiliary lanes is more likely to decrease the probability of severe injuries of single-motorcycle crashes on horizontal curves by 4.51%. Auxiliary lanes extend pavement width to provide more negotiation space for motorcyclists and usually are linked to access points, which tend to cause rider safety compensation behaviors (e.g., reducing speed) for avoiding potential conflicts.

Vegetation and paved medians are more likely to result in severe injuries in curve-related single-motorcycle crashes, and rider negative safety compensation behaviors (safety compensations) may be the cause. These two kinds of medians psychologically increase the negotiation space for riders, who may feel more confident in curve negotiation and intend to use injury-deteriorating behaviors (e.g., increasing speed, careless riding). Safety compensation effects were explored by numerous studies [14], [16], [19]–[21]. Based on the sample, average speeds in motorcycle crashes with vegetation and paved medians are 55.9 mph and 51.8 mph, respectively; speed values with non-vegetation and non-paved median are 46.1 mph and 39.3 mph, respectively.

Single-motorcycle crashes that occur on full-access-controlled curves tend to have a lower probability of severe injuries compared to non-access-controlled curves. However, full-access-controlled roads usually have higher running speeds, which is a significant injury-deteriorating factor. This effect is possible for several reasons. First, compared to other roads, full-access-controlled roads have a higher design standard for horizontal curves (e.g., sharpless curve design, wide lane width, large clearance space on medians or shoulders).

Thus, the complexity of curve negotiation on full-access-controlled roads is lower than others, and riders have more opportunities to avoid injury-deteriorating crashes (e.g., hitting on fixed objects). Second, riders traveling on full-access-controlled roads are more likely to take injury-mitigating behaviors (e.g., wear a helmet, less alcohol/drug impairment). In addition, the percentage of invulnerable riders (e.g., young, male) using full-access-controlled roads is higher than those using non-access-controlled roads. The sample data analysis supported these inferences (full-access control vs. non-access control): sharp curve, 7.6% vs. 34.7%; helmet use, 72.4% vs. 58.8%; alcohol/drug impairment, 4.7% vs. 12.4%; young rider, 42.5% vs. 32.5%; male, 94.3% vs. 90.8%). A similar discussion of safety compensation effects for motorcycle crashes on interstates was found in a previous study conducted by Shanker and Mannering [14].

4.3.4 Pavement

The effects of negative safety compensation effects are significant for the three pavement factors (pavement condition, roughness index, friction). Single-motorcycle crashes on

curves with poor pavement conditions (pavement condition index < 3, roughness index > 80, or friction number ≤ 45) are more likely to have a lower probability of severe injuries compared to curves with good pavement conditions. Riders likely will use injury-mitigating riding behaviors (e.g., reduce speed, careful riding) if they psychologically lack confidence on poor pavement. Geedipally et al. [19] reached a similar conclusion, that good surface conditions increase the probability of fatal and incapacitating injury by encouraging vehicle speeding.

4.3.5 Environment

Dry road surfaces increase the probability of severe injuries in single-motorcycle crashes on curves by 11.42% because they encourage motorcyclists to use injury-deteriorating behaviors by riding at a high speed. This finding is consistent with previous studies [13], [16].

Darkness is likely to increase the probability of severe injuries in single-motorcycle crashes on curves, which is in line with previous studies [11], [12], [15]–[19]. This could be the result of a number of factors: (1) darkness will decrease the sight distance of motorcycle riders and increase the difficulty of looking through the horizontal curve; (2) because of the low volume of traffic at night, motorcycle riders may take more risk behaviors by riding at a high speed; (3) alcohol- or drug-impaired riders typically are self-selected risk takers in darkness; and (4) motorcyclists with lower helmet use and safety awareness also typically are self-selected risk takers in darkness. Street lighting mitigates the injury of motorcyclists on curves due to improved sight distance. Darkness with lights, as shown in Figure 6, will decrease the probability of severe injuries by 2.3% (42.9% - 40.6%), compared to darkness.

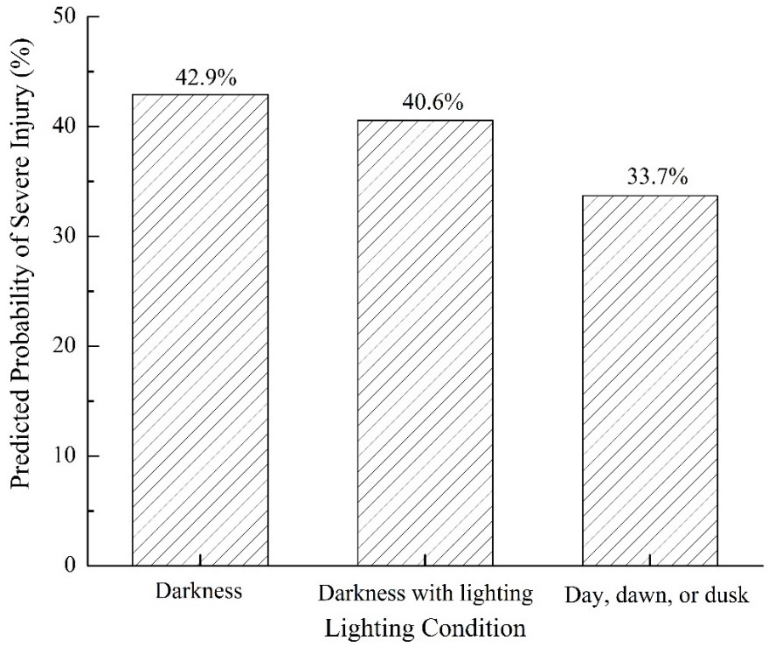

Figure 7 – Predicted Probability of Severe Injury by Lighting Condition

4.3.6 Crash Characteristics

Collisions with a concrete barrier wall, tree, and other-fixed object are more likely to increase the likelihood of severe injuries in single-motorcycle crashes on curves by 20.55%, 15.62%, and 7.51%, respectively. Hitting fixed objects is likely to transfer more kinetic energy to motorcyclists. This finding is consistent with previous studies [14], [16], [22]–[24].

Alcohol or drug impairment, which degrades rider ability to safely negotiate curves and increases inherent risk-taking tendencies, increases the probability of severe injuries for single-motorcycle crashes on curves by 7.20%. This finding is in line with previous studies [11]–[16], [18], [22]. Proper riding, which captures rider inherent safety awareness, decreases the probability of severe injury by 11.90%, and helmet use decreases the likelihood of severe injury by 8.35%. This effect is also supported by previous studies [11], [13], [15], [16].

Single-motorcycle crashes occurring on weekends are more likely to result in severe injuries. Shaheed and Gkritza reported similar findings [13]. Motorcyclists are more likely to ride recklessly and have less safety awareness on weekends. Based on the sample data, the percentage of helmet use on weekends is 58.99%, which is significantly lower than that on weekdays (66.02%).

4.3.7 Rider Characteristics

Compared to adult and older riders, young riders (age < 30) have much better perception of curves and higher tolerance to injuries. As indicated in previous studies [13], [15], [19], young riders are less likely to suffer severe injuries in single-motorcycle crashes on curves by 5%.

The parameter related to older riders (age ≥ 60) is random and normally distributed, with a mean of 0.721 and a standard deviation of 1.382. This suggests that, on average, about 69.9% of older riders involved in a curve-related single-motorcycle crash are more likely to experience severe injuries; the remaining 30.1% are less likely to suffer severe injuries (Eq. 4). The random effects of older riders could be caused by (1) unobserved heterogeneity related to older rider physiological conditions and injury tolerances and (2) unobserved heterogeneity related to older rider driving experience and familiarity with road environment. On average, older riders tend to increase the probability of incurring severe injury in curve-related single motorcycle crashes by 16.27%. The vulnerability of older riders was reported in previous studies [14], [16], [22] but it was considered a fixed parameter.

The male indicator is also normally distributed, with a mean of -0.206 and a standard deviation of 2.390, suggesting that 53.4% of male riders are less likely to experience severe injuries in curve-related single-motorcycle crashes (Eq. 4). However, 46.6% of male riders are more likely to be involved in crashes involving severe injuries. Usually, the injury tolerance of a male is higher than that of a female. In contrast, male riders are more likely to take risk-seeking behaviors than female riders. The random effects of male riders reflect the variance of male riders in physiological characteristics and risk-seeking intentions. Since the difference between the two effects are not very significant (53.4% vs. 46.6%), the

overall marginal effects of male riders are insignificant (*t*-statistics = -1.36, Table 4). Previous studies have contradictory insights on the impact of gender—some researchers indicated that male riders are more likely to increase the injury severity of motorcycle crashes [11], [17]–[19], but others stated that male riders tend to decrease the likelihood of severe injuries in a motorcycle crash [13].

Chapter 5
Crash Modification Factors Development using Case-Control Method

5.1 Data Collection and Descriptive Statistics

As described in Chapter 2, the case-control method has a different data collection scheme from the cross-sectional method. In this study, the data collection procedure for the case-control study is give in Figure 8.

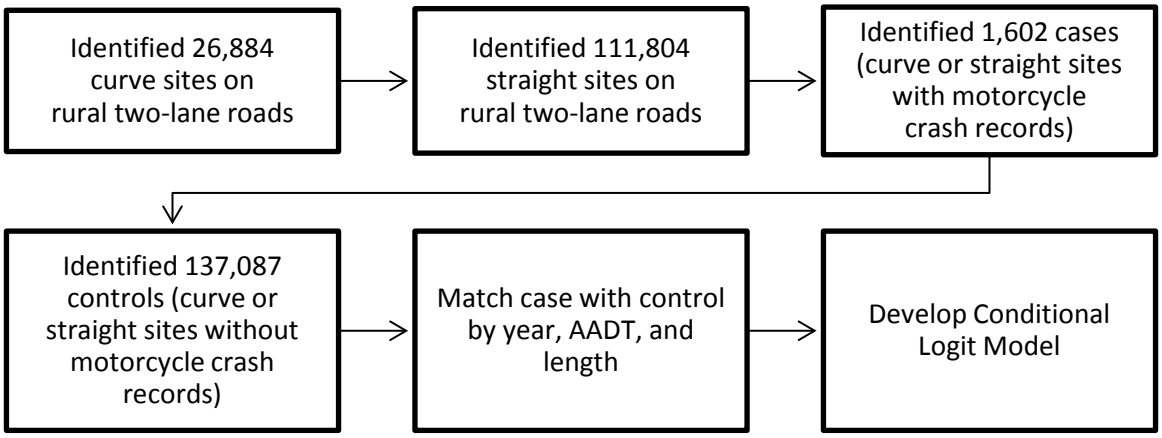

Figure 8 – Procedure for Case-Control Data Collection

In total, 1,602 cases were matched to 16,020 controls with similar year, AADT, and length. The 1:10 control/case ratio can make the power of case-control study reaching 99%. The descriptive statistics of risk factors is given in Table 6.

Table 6 – Descriptive Statistics of Risk Factors for Case-Control Study

Variable Description	Mean	Std Dev
Sharp curve indicator (1 if radius of curve is less than 1,000 ft, 0 otherwise)	0.012	0.110
Moderate curve (1 if radius of curve is between 1000 ft and 2000 ft, 0 otherwise)	0.046	0.210
Flat curve (1 if radius of curve is between 2000 ft and 10,000 ft, 0 otherwise)	0.121	0.326
Straight segment (1 if radius of curve is greater than 10,000 ft or tangent, 0 otherwise)	0.821	0.384
Vertical slope indicator (1 if vertical slope exists in the segment, 0 otherwise)	0.094	0.292
Principal arterial indicator (1 if functional classification is principal arterial, 0 otherwise)	0.368	0.482
Auxiliary lane indicator (1 if auxiliary lane exists in the segment, 0 otherwise)	0.060	0.238
Access ability indicator (1 if access density of roadway is greater than zero, 0 otherwise)	0.576	0.494
Higher speed limit indicator (1 if speed limit is greater than 50 mph, 0 otherwise)	0.735	0.441
Narrow surface width indicator (1 if surface width is less than 24 ft, 0 otherwise)	0.246	0.431
Narrow shoulder width indicator (1 if shoulder width is less than 12 ft, 0 otherwise)	0.448	0.497
Paved shoulder type (1 if shoulder type is paved or paved with warning device, 0 otherwise)	0.745	0.436
Poor pavement indicator (1 if pavement condition is less than 3, 0 otherwise)	0.266	0.442

5.2 Model Estimation

The conditional logit model was estimated based on the collected case-control data. The fitted model is given in Table 7.

Table 7 - Matched Case-Control Model for Motorcycle Crashes on Rural Two-lane Highways

Variable Description	Estimated Parameter	*t*-Statistic	Odds Ratio (CMF)
Sharp curve indicator (1 if radius of curve is less than 1,000 ft, 0 otherwise)	1.185	4.70	3.27
Moderate curve (1 if radius of curve is between 1000 ft and 2000 ft, 0 otherwise)	1.091	7.47	2.98
Flat curve (1 if radius of curve is between 2000 ft and 10,000 ft, 0 otherwise)	0.598	4.75	1.82
Straight segment (1 if radius of curve is greater than 10,000 ft, 0 otherwise)	-	-	-
Vertical slope indicator (1 if vertical slope exists in the segment, 0 otherwise)	0.402	4.57	1.50
Principal arterial indicator (1 if functional classification is principal arterial, 0 otherwise)	0.761	11.03	2.14
Auxiliary lane indicator (1 if auxiliary lane exists in the segment, 0 otherwise)	0.439	4.62	1.55
Access ability indicator (1 if access density of roadway is greater than zero, 0 otherwise)	0.664	10.71	1.94
Higher speed limit indicator (1 if speed limit is greater than 50 mph, 0 otherwise)	0.454	5.40	1.58

Narrow surface width indicator (1 if surface width is less than 24 ft, 0 otherwise)	-0.598	-5.75	0.55
Narrow shoulder width indicator (1 if shoulder width is less than 12 ft, 0 otherwise)	-0.140	-2.19	0.87
Paved shoulder type (1 if shoulder type is paved or paved with warning device, 0 otherwise)	1.003	8.96	2.73
Poor pavement indicator (1 if pavement condition is less than 3, 0 otherwise)	-0.277	-3.34	0.76
Model Statistics			
Number of observations	17,622		
Restricted log likelihood	-3841.43		
Log-likelihood at convergence	-3385.78		
McFadden pseudo R-squared (ρ^2)	0.119		

5.3 CMF for Curve Radius

The probabilities of a motorcycle crash occurring on sharp curve (R<1000 ft), moderate curve (1000<R≤2000 ft), and flat curve (2000<R<10,000 ft), relative to the probability of a motorcycle crash occurring on tangent segments, increase by about 227%, 198%, and 82%, respectively.

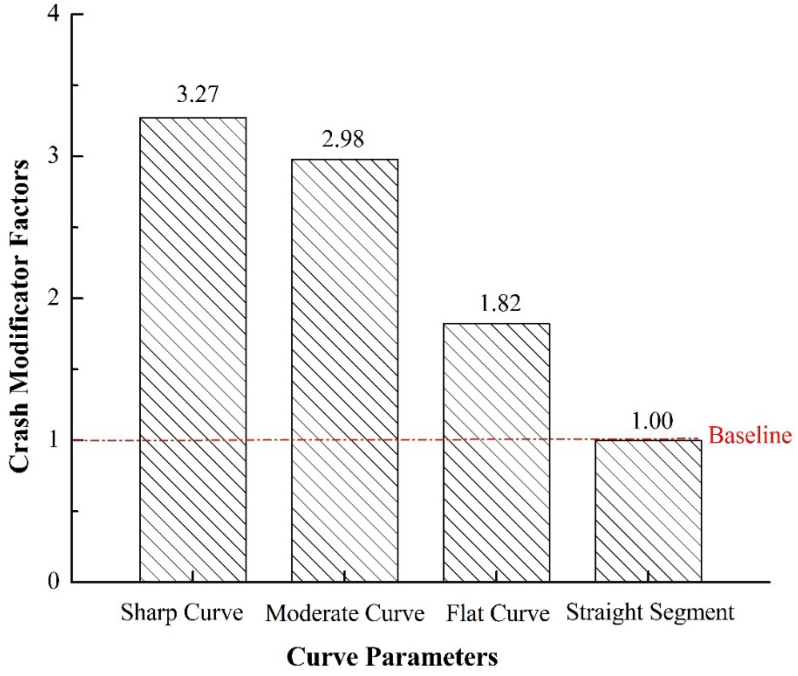

Figure 9 – Crash Modification Factors of Horizontal Curve Radius for Motorcycle Crash on Rural Two-Lane Highway

Chapter 6
Summary and Conclusions

Task 3 investigated the effects of horizontal curvature and associated factors (geometric, traffic, vehicle, and riders) on motorcycle crashes on horizontal curves in Florida. Two mixed-effects regression models—mixed-effects negative binomial model and mixed-effects logistics model—were used to fit the crash-frequency and crash-severity data, respectively. The significant factors contributing to motorcycle crashes on horizontal curves are summarized in Table 8.

Table 6 – Risk Factors of Motorcycle Crashes on Horizontal Curve Segments

Risk Factors on Horizontal Curves	Effect on Motorcycle Crash Occurrence	Effect on Motorcycle Crash Severity	Cause Analysis	Suggested Countermeasures
Sharp Curve (R<1500 ft)	⇧	⇧	• Increased speed variation • Decreased sight distance • Increased complexity of negotiation maneuver	• Increase curve radius • Advance curve warning & advisory speed signing • Chevrons & enhanced chevron signs • Dynamic curve warning system
Reverse Curve	⇩	⇧	• Promotion of safety-compensation behavior (e.g., reduce speed) • Increased complexity of negotiation maneuver (e.g., run off the road)	• Reverse curve warning & advisory speed signing • Chevrons & enhanced chevron signs • Flashing beacons
Higher Speed (>50 mph)	⇧	⇧	• Reduced time of response • Increased complexity of negotiation maneuver • Increased kinetic energy dissipation to motorcycle rider's body	• Dynamic speed feedback sign with posted speed • SLOW sign (e.g., on-pavement curve signing)
Speeding	⇧	⇧	• Geometric design barrier • Reduce time of response • Increase kinetic energy dissipation to motorcycle rider's body	• Dynamic speed feedback sign with posted speed • Enforcement countermeasure
Auxiliary Lane	⇧	⇩	• Increased potential traffic conflicts • Promotion of safety-compensation behavior (e.g., reduce speed)	• Longitudinal channelizers • Pavement marking
Surface (Shoulder) Width	---	⇧	• Promotion of safety-compensation behavior (e.g., increase speed)	• Road markings that make road look narrower (e.g., chevron markings, transverse shoulder stripes)

Full Access Control	⇩	⇩	• Higher design standards for horizontal curves • Decreased potential traffic conflicts • Strict enforcement environment • Promotion of safety-compensation behavior (e.g., helmet use) • Self-selectivity group (e.g., young, male rider)	• Enforcement countermeasure (e.g., helmet use)
Rough (Poor) Pavement	---	⇩	• Promotion of safety-compensation behavior (e.g., reduce speed) • Increased rider alertness	• Road markings that make road look rougher • Transverse rumble stripes
Lighting	---	⇩	• Improved sight distance • Decreased complexity of negotiation maneuver	• Lighting installment (e.g., in-pavement lighting, reflective barrier delineation)

In addition, the research team developed Crash Modification Factors/Functions of horizontal curve radius for motorcycle crashes on rural two-lane roadways using two different methods: cross-sectional and case-control.

- Crash Modification Functions by Cross-sectional Method

$$CMF = \left(\frac{R}{5000}\right)^{-0.208}$$, R is curve radius in ft; baseline is 5000 ft

- Crash Modification Factors by Case-Control Method

Curve Radius (R)	CMF (baseline is straight segment)
R ≤ 1,000 ft	3.27
1,000 ft < R ≤ 2,000 ft	2.98
2,000 ft < R ≤ 10,000 ft	1.82

The two CMFs have the same trend but their baselines are different. Considering the case-control method can effectively address confounding variables and low-mean sample, the CMF-developed case-control method is preferred.

References

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