Development of crash modification factors of horizontal curve design features for single-motorcycle crashes on rural two-lane highways: A matched case-control study

Chunfu Xin[a], Zhenyu Wang[b],*, Chanyoung Lee[b], Pei-Sung Lin[b], Tao Chen[c], Rui Guo[d], Qing Lu[a]

[a] Department of Civil and Environment Engineering, University of South Florida, 4202 E. Fowler Avenue, ENB118, Tampa, FL, 33620, USA
[b] Center for Urban Transportation Research, University of South Florida, 4202 E. Fowler Avenue, CUT100, Tampa, FL, 33620, USA
[c] Key Laboratory of Automotive Transportation Safety Techniques of Ministry of Transport, Chang' an University, 2nd Ring Road South East Section, Xi'an, Shanxi 710064, China
[d] Civil, Environmental, and Construction Engineering, Texas Tech University, 2500 Broadway, Lubbock, TX, 79409, USA

ABSTRACT

Single-motorcycle crashes are overrepresented on horizontally curved segments of rural, two-lane, undivided (RTU) highways. However, the relationship between single-motorcycle crash risk and the design features of horizontal curves on RTU highways is not well-studied in existing literature. This study aims to quantify the effect of horizontal curve type and radius on the risk of single-motorcycle crashes with a matched case-control study that can address the issues of the low sample mean, aggregation bias, and uncontrolled confounders existing in the traditional cross-sectional study. In the matched case-control study, three matching factors—year, annual average daily traffic (AADT), and segment length—were selected to match controls (RTU segments without crash records) with cases (RTU segments with crash records). A total of 1601 cases and 16,010 matched controls over 11 years (2005–2015) were identified as matched-strata. A conditional logistic model was fitted on the matched-strata data to estimate the crash modification factors (CMFs) of horizontal curve design features for single-motorcycle crashes. The modeling results highlighted the interaction effects between curve type and radius on the risk of single-motorcycle crashes. Sharp (radius ≤ 1500 ft) non-reverse curves were identified as the riskiest curve design for motorcyclists, followed by sharp reverse curves and moderate (1500 ft < radius ≤ 3000 ft) reverse curves. The study also revealed that motorcyclists might take safety-compensation behaviors on sharp curves, narrow shoulders, and poor pavement conditions. Engineering and education countermeasures are suggested for comprehending curve presence and associated risk level, reducing curve entry speed, and improving safety awareness. Finally, the limitations of the study and possible solutions are discussed.

1. Introduction

Horizontal curves are a fundamental design element of a highway system, which pose a critical issue in transportation safety management (Torbic et al., 2004). The Federal Highway Administration (FHWA) reported that more than 25% of fatal crashes are related to horizontal curves (FHWA, 2018). Single-motorcycle crashes are even more overrepresented on horizontal curves, particularly concerning fatalities or incapacitating-injuries. For example, in Florida, approximately 57% of fatal single-motorcycle crashes and 36% of incapacitating single-motorcycle crashes occur on horizontal curve segments, which constitute only about 6% of the total mileage of the Florida highway system (Wang et al., 2014). Because of the predominance of horizontal curves on rural two-lane undivided (RTU) highways, a large proportion of single-motorcycle crashes occur on these segments. Relative to interstate highway facilities, horizontal curve segments of RTU highways have the following safety concerns for motorcyclists (Xin et al., 2017b, 2018): (1) lower traffic volume; (2) lower safety standards for highway design; (3) more complex geometric features; and (4) more attractive to risk-seeking behaviors (Shankar and Mannering, 1996). These safety risk factors combined with erroneous riding behaviors (e.g., underestimation of curve sharpness, excessive speed, wrong lean angle, understeering, and over-braking) may increase single-motorcycle crashes on RTU horizontal curve segments.

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* Corresponding author.
E-mail addresses: chunfu@mail.usf.edu (C. Xin), zwang9@cutr.usf.edu (Z. Wang), cylee@cutr.usf.edu (C. Lee), lin@cutr.usf.edu (P.-S. Lin), chentao@chd.edu.cn (T. Chen), rui.guo@ttu.edu (R. Guo), qlu@usf.edu (Q. Lu).

In recent years, as noted in two papers (Xin et al., 2017a, 2017b), efforts have been made to address motorcycle safety issues on horizontal curve segments regarding crash occurrence and injury outcomes. However, most previous studies explored the safety effects of the presence of horizontal curves on motorcycle crashes; only a few were found to investigate the association between motorcycle crash occurrence and curve design features. To be specific, in 2010, Schneider et al. (2010) developed a negative binomial (NB) model for single-motorcycle crash frequency on rural two-lane highways in Ohio. In their study, 225 single-motorcycle crashes were identified from 30,379 roadway segments between 2002 and 2008. They found that a 1% increase in curve radius would linearly reduce the average single-motorcycle crash frequency by 0.74%. Gabauer and Li (2015) investigated the effects of horizontally-curved roadway section characteristics on motorcycle-to-barrier crashes in Washington State using an NB model. In their study, 329 motorcycle-to-barrier crashes were identified from 4915 roadway segments between 2002 and 2011. They found that isolated curves, decreases in curve radius, and increases in curve length would increase the risk of motorcycle-to-barrier crashes. To address the unobserved heterogeneity issue, Xin et al. (2017b) quantified the effects of horizontal curve design features on single-motorcycle crash frequency along RTU highways with a random parameters NB model. In their study, 439 single-motorcycle crashes were identified from 2,176 roadway segments between 2005 and 2015. They found that the single-motorcycle crash frequency would reduce logarithmically with the increase of horizontal curve radius, and the presence of a reverse curve has random effects on single-motorcycle crash frequency.

However, issues exist in the above studies. First, due to very few motorcycle exposures on rural highways, most horizontal curve segments of rural highways have not experienced a motorcycle crash over one year. With low sample-means of motorcycle crashes, the distribution of crash counts would be skewed excessively toward zero, which can result in incorrect parameter estimates of the NB models (Lord and Mannering, 2010). Second, to increase the sample mean of single-motorcycle crashes, a long observation period was used in the studies (7, 10, and 11 years), which may lead to temporal variation and a bias estimation in the NB models (Washington et al., 2010). Third, since few curve upgrade projects could be identified in a reasonable period for the before-after study, the above three studies were conducted with cross-sectional observations. Observational cross-sectional studies without any control for confounding factors may not successfully identify the cause-effect relationships between motorcycle crashes and roadway characteristics (Hauer, 2010).

To address the low mean problem, aggregation bias, and uncontrolled confounding effects, this study aimed to develop the crash modification factors (CMFs) of horizontal curve features for single-motorcycle crashes with a matched case-control study.

The remainder of this paper is structured as follows. Section 2 illustrates the matched case-control study design and its modeling approach. Section 3 presents data preparation and descriptive statistics for the matched case-control study. Section 4 describes the empirical estimation results of the conditional logistic regression model and odds ratios. Section 5 discusses the effects of risk factors on single-motorcycle crashes. Finally, Section 6 summarizes the major findings and provides recommendations to improve curve-related motorcycle safety.

2. Matched case-control study

A matched case-control study is commonly used in epidemiology to quantify the risk of disease given specific characteristics related to an individual (Schlesselman, 1982). Recently, it has been used in the highway safety field to investigate the risk of vehicle crashes given specific characteristics related to a highway segment (Abdel-Aty et al., 2004; Davis et al., 2006; Gross, 2013; Gross and Donnell, 2011; Gross and Jovanis, 2007). Unlike a cross-sectional study proceeding from cause to effect, this method adopts a different procedure (from effect to

cause) in an attempt to identify pre-condition contributing factors to crash outcomes. The steps of a matched case-control study are as follows:

- *Step 1–Defining*: Highway segments are split into two groups: 1) case—a highway segment that experienced at least one crash in a given period, and 2) control—a highway segment that did not suffer a crash in the same period.
- *Step 2–Matching*: Multiple controls are randomly matched to each case based on the similarity of confounding variables that are correlated to both the risk factors of interest (e.g., curve features) and the outcomes (e.g., single-motorcycle crashes). This matching scheme is intended to eliminate the biased estimations on the association between the risk factor of interests and the outcomes through mitigating the disturbance from confounders (Schlesselman, 1982). An increase in the ratio of controls to cases will increase the power of the study, particularly if the number of cases is relatively few (Groos et al., 2010). In addition, since it is often impractical to match the exact value for confounding variables, a category-matching scheme is usually implemented to stratify each of the variables and randomly pair cases and controls that fall into the same cell created by the multiple cross-classification. The control-to-case ratio of the study is determined by the minimum ratio of controls to cases among all cross-classification categories.
- *Step 3–Modeling*: A conditional logistic regression model is estimated with the matched case-control strata. Based on the estimated coefficients, the odds ratio can be calculated to quantify the relative risk of unmatched variables (i.e., curve features and other geometric variables) on single-motorcycle crashes, which is different from the expected probability of a single-motorcycle crash (Groos et al., 2010.

2.1. Matched case-control study design

The design approach of a matched case-control study has some distinctive features, which make it more valid to infer causality than a cross-sectional study. First, due to a pre-specified number of cases enrolled in the study, a matched case-control study design is robust in studying rare events (Woodward, 2013). This feature is valuable for addressing the low mean problem and aggregation bias issue in the previous cross-sectional motorcycle safety studies. Second, the matched case-control study design adopts a control group to support or refute an inference of a cause for any risk factor. The matching design can directly address the uncontrolled confounding effects since each matched stratum has similar values for each confounding variable (Schlesselman, 1982). Third, the matched sampling approach in a matched case-control study leads to a balanced number of cases and controls, which can reduce the variance in the parameters of interest and improve statistical efficiency in model estimation (Sahai and Khurshid, 1995).

Although a matched case-control study is a powerful tool to address the association between risk factors and outcomes, careful design is needed to avoid the following issues that may result in biased parameter estimates and inferences.

2.1.1. Overmatching

Matching variables should be true confounders that associate with both the risk factors of interest and the outcomes. If matching variables are associated only with one, the stratification process of matching variables will also involve the stratification of the risk factors of interest or outcomes. Thus, the relationship between the exposure and the outcome will be obscured (Marsh et al., 2002). Also, when matching more than one variable, matching variables should not be strongly correlated with each other (Schlesselman, 1982).

2.1.2. Residual confounding

If the stratification of matching variables is too loose, the effects of confounding factors cannot be eliminated from the risk-outcome effect of interest (Psaty et al., 1999). On the other hand, if matching too many confounders, the control-to-case ratio in each matching cell would decrease dramatically, which will reduce the power of design (Woodward, 2013). In practice, to avoid insufficient controls, a trade-off analysis of the number of matching variables should be made based on statistical analysis and professional knowledge.

2.1.3. Selection bias

If the selection criteria of highway segments (i.e., cases or controls) are related to the risk factor of interest, the assumption for estimating the odds ratio with the conditional logistic regression model—the probability of selection of cases and controls is independent of covariates—will be violated (Lin and Paik, 2001). Under such a situation, the highway segments in the sample cannot represent the real population, which will result in a biased inference.

2.2. Analytic method for matched case-control study

The conditional logistic regression is an extension of the logistic regression that accounts for stratification in matched case-control studies (Breslow et al., 1978). The dependent variable y_{ij} is a binary variable indicating whether single-motorcycle crashes on the jth segment in the ith stratum during the observation period occur or not: $y_{ij} = 1$ if it is a case; or $y_{ij} = 0$ if it is a control. The probability of single-motorcycle crash occurrence is expressed as

$$Pr(y_{ij} = 1) = 1 / \left\{ 1 + exp\left[-\left(\alpha_i + \sum_k \beta_k x_{ijk} \right) \right] \right\} \quad (1)$$

where x_{ijk} is the kth unmatched explanatory variable associated with the jth segment in the ith stratum; α_i is the stratum-specific interpretation term reflecting the different combination effects of confounding variables for different strata; and β_k is the estimated coefficients for unmatched explanatory variables.

The conditional likelihood for each stratum i is based on the matched case-control design that the case is the one with the row vector x_{i0} and the controls are those with the other row vectors x_{ij} ($j = 1, 2, \cdots, J$) for k unmatched explanatory variables; J is the number of controls in a stratum. Because each observation within the stratum shares the same characteristics of confounding variables, the effects of confounding variables on conditional probability cannot be estimated. The conditional likelihood $L(Y_i|\beta_k)$ of the stratum i can be calculated as

$$L(Y_i|\beta_k) = \left[1 + \sum_j exp\left(\sum_k \beta_k (x_{ijk} - x_{i0k}) \right) \right]^{-1} \quad (2)$$

where x_{i0k} is the value of x_k for a case (segment with single-motorcycle crashes) in the ith stratum, and x_{ijk} is the value of x_k for the jth matched control (segment without single-motorcycle crashes) in the ith stratum. Because the strata are assumed to be independent from each other, the conditional log-likelihood function $LL(Y|\beta_k)$ can be written as (Schlesselman, 1982):

$$LL(Y|\beta_k) = -\sum_i ln\left[1 + \sum_j exp\left(\sum_k \beta_k (x_{ijk} - x_{i0k}) \right) \right] \quad (3)$$

Because the interpretation term α_i in Eq. (1) cannot be estimated, the absolute probability of single-motorcycle crash occurrence cannot be calculated in a matched case-control study. Alternatively, the odds ratio (OR) is calculated to evaluate the change of the relative risk of single-motorcycle crashes due to a change in an unmatched explanatory variable. For a dummy variable, the odds ratio is a statistic defined as the ratio of the odds of the case in the presence of a roadway characteristic k ($x_k = 1$) and the odds of the case without the presence of a roadway characteristic k ($x_k = 0$). The odds ratio for a dummy variable (x_k) can be written as

$$OR(x_k) = \frac{Pr(y_{i0} = 1, \ x_k = 1, \ Z) / [1 - Pr(y_{i0} = 1, \ x_k = 1, \ Z)]}{Pr(y_{i0} = 1, \ x_k = 0, \ Z) / [1 - Pr(y_{i0} = 1, \ x_k = 0, \ Z)]}$$
$$= exp(\beta_k) \quad (4)$$

where Z represents the vector of explanatory variables other than x_k, and β_k is the estimated coefficient for x_k. Based on the definition, the odds ratio can be used as the direct estimation of the crash modification factor (CMF).

3. Data collection

3.1. Data preparation

The Florida Roadway Characteristics Inventory (RCI) is a comprehensive database containing Florida roadway information by year, including geographic location, geometric characteristics, pavement condition, and traffic volume (Florida Department of Transportation [FDOT], 2016). The data field HRZDGCRV in the RCI database indicates the horizontal degree of curvature that is measured by the subtended angle at the center by an arc of 100 ft. The degree of curvature (D) was retrieved from the RCI database for each curved segment and converted to the radius of curvature (R at ft) by $R = 5729.6/D$. The curve type of each curved segment was identified as reverse curve or non-reverse curve with the Google Maps. As shown in Fig. 1, a reverse curve consists of two simple curves that join in opposite directions. A non-reverse curve can be a simple curve or a compound curve that consists of two simple curves with deflections in the same direction immediately adjacent to each other.

A total of 2444 curved segments (with a 300-ft buffer on each end)

Fig. 1. Horizontal Curve Types.

and 10,164 straight segments were identified on Florida RTU highways with the following criteria: (1) all segments were in a rural area; (2) all segments were two-lane roads without median; (3) each segment had homogeneous roadway characteristics; (4) segment length was 600 ft or more; and (5) no signalized intersections existed. To avoid selection bias, the sample of horizontal curves was determined with a sufficiently random sampling procedure. For each roadway segment, a series of roadway characteristics (e.g., speed limit, shoulder type, shoulder width, pavement condition, vertical slope) were retrieved from the Florida RCI database by year (2005–2015).

The Florida Crash Analysis and Reporting (CAR) system stores all traffic crash records in Florida. Single-motorcycle crashes that involved only one motorcycle (no other vehicles or pedestrians involved) and occurred between 2005 and 2015 were retrieved from the CAR system and were spatially matched to curved segments and straight segments by year (2005–2015). In total, 439 and 1265 single-motorcycle crashes were assigned to curved and straight segments, respectively. The descriptive statistics of the collected variables for horizontal curve segments and straight segments over 11 years are shown in Tables A1 and A2 in the Appendix A, respectively.

3.2. Case and control definition

A case was defined as an RTU highway segment that experienced at least one single-motorcycle crash in a specific year. A control was defined as an RTU highway segment that did not experience any single-motorcycle crash in a specific year. Each selected RTU highway segment was allocated as a case or a control for each year. One physical roadway segment might be a case or a control in different years. The numbers of cases and controls in the study population are shown in Table 1. The study population contained 12,608 roadway segments (2444 curved segments and 10,164 straight segments) in each year, with only about 1% of roadway segments experiencing a motorcycle crash (a preponderance of zero-crash segments).

3.3. Confounder matching

Annual average daily traffic (AADT) and segment length are two typical confounders connecting to geometric designs (Gross and Jovanis, 2007). To be specific, AADT as an exposure variable has been shown to be a significant predictor of single-motorcycle crash risk (Schneider et al., 2010; Xin et al., 2017b). Minimum curve radius is a function of design speed, which is determined by design traffic volume (AASHTO, 2001). High-traffic RTU highways are more likely to be designed with a large horizontal curve radii. The segment length directly associates with motorcycle vehicle miles traveled (VMT), which can significantly influence single-motorcycle crash risk on a highway segment (Schneider et al., 2010; Xin et al., 2017b). The segment length also associates with curve type. Reverse curves combining two or more single curves usually accompany relatively long segment length. If the

Table 1
Numbers of Cases and Controls in Study Population by Year.

Year	Case Segments	Control Segments	Total Segments
2005	121	12,487	12,608
2006	139	12,469	12,608
2007	169	12,439	12,608
2008	184	12,424	12,608
2009	153	12,455	12,608
2010	157	12,451	12,608
2011	146	12,462	12,608
2012	160	12,448	12,608
2013	156	12,452	12,608
2014	136	12,472	12,608
2015	80	12,528	12,608
Total	**1,601**	**137,087**	**138,688**

Table 2
Match Categories and Sample Sizes for AADT and Segment Length.

Segment Length (ft)	AADT (vehicles/day)					
	< 2000	2000-4000	4000-6000	6000-8000	> 8000	Total
600-1500	363	583	143	242	341	1,672
1500-2500	627	1,221	1,043	825	880	4,587
2500-3500	1,034	1,232	880	704	616	4,466
3500-4500	792	1,045	462	374	209	2,882
> 4500	825	1,298	968	649	264	4,004
Total	3,641	5,379	3,487	2,794	2,310	17,611

confounding effects of AADT or segment length are not addressed, the real effects of horizontal curve design features on single-motorcycle crashes may be masked.

Matching AADT and segment length between cases and controls was conducted within each year. The year indicator is a surrogate measure of temporal variations of unobserved confounding factors. For example, safety-related riding behaviors associated with curve features may change over years caused by other treatments (e.g., motorcycle safety campaigns). However, information on other treatments is unobserved in the crash database. Matching controls to cases by year can mitigate the confounding effect of temporal-varied factors on the risk of single-motorcycle crashes.

To avoid insufficient controls for matching and correlation interference among matching variables, other potential confounders (e.g., speed limit) were treated as covariates in the conditional logistic model. Match categories and sample sizes for AADT and segment length by year are presented in Table 2.

In the study, 1601 case-control strata (1601 cases, 16,010 controls) were identified for modeling. The control-to-case ratio of 10 would achieve approximately 98% power of design (Woodward, 2013). To validate the matching design process, the statistical distribution of matched confounders (AADT and segment length) for cases and controls were compared and illustrated as follows. The mean value and standard deviation of AADT for cases (controls) were 6082 (5903) and 3897 (3917) vehicles per day, respectively. In addition, the mean value and standard deviation of segment length for cases (controls) were 3049 (3063) and 2452 (2665) ft, respectively. The design of two-confounders matching by year and the fitting of covariates in the conditional logistic model can effectively address the issue of overmatching and residual confounding.

3.4. Descriptive statistics

The descriptive statistics of unmatched risk factors (e.g., curve features, roadway characteristics, and geographical characteristics) for cases and controls are given in Table 3. The matched case-control study indicates the likelihood of a potential risk factor by assessing whether it is disproportionally distributed between the cases and controls. For example, as shown in Table 3, about 4.5% of roadway segments that experienced at least one single-motorcycle crash were sharp non-reverse curves, whereas only 1.9% of roadway segments that did not experience a single-motorcycle crash were sharp non-reverse curves. Thus, a sharp non-reverse curved segment is more likely to increase the risk of single-motorcycle crash occurrence. To examine and quantify the risk associated with one factor while controlling for other factors, a conditional logistic model was developed, as discussed in the next section.

4. Model estimation

The software package SPSS 23.0 (IBM, 2015) was used to estimate the conditional logistic regression model based on the matched case-

Table 3
Descriptive Statistics of Key Variables in Matched Case-Control Study.

Variable Description	Case (n = 1601)		Control (n = 16,010)	
	Mean	Standard Deviation	Mean	Standard Deviation
Sharp reverse curve indicator (1 if radius of reverse curve is less than 1500 ft, 0 otherwise)	0.008	0.090	0.006	0.076
Sharp non-reverse curve indicator (1 if radius of non-reverse curve is less than 1500 ft, 0 otherwise)	0.045	0.207	0.019	0.135
Moderate reverse curve indicator (1 if radius of reverse curve is between 1500 ft and 3000 ft, 0 otherwise)	0.016	0.124	0.012	0.108
Moderate non-reverse curve indicator (1 if radius of non-reverse curve is between 1500 ft and 3000 ft, 0 otherwise)	0.073	0.260	0.063	0.243
Slight curve indicator (1 if radius of curve is between 3000 ft and 8000 ft, 0 otherwise)	0.077	0.266	0.072	0.258
Flat curve indicator (1 if radius of curve is between 8000 ft and 20,000 ft, 0 otherwise)	0.022	0.148	0.024	0.153
Straight segment indicator (1 if radius of roadway segment is over 20,000 ft, 0 otherwise)	0.759	0.428	0.805	0.397
Vertical slope indicator (1 if vertical slope exists in the roadway segment, 0 otherwise)	0.155	0.362	0.096	0.295
Auxiliary lane indicator (1 if auxiliary lane exists in the segment, 0 otherwise)	0.106	0.307	0.052	0.223
Accessibility indicator (1 if access density of roadway is greater than zero, 0 otherwise)	0.687	0.464	0.557	0.497
Higher speed limit indicator (1 if speed limit is greater than 50 mph, 0 otherwise)	0.845	0.362	0.731	0.444
Narrow surface width indicator (1 if surface width is less than 24 ft, 0 otherwise)	0.108	0.311	0.232	0.422
Narrow shoulder width indicator (1 if shoulder width is less than 12 ft, 0 otherwise)	0.395	0.489	0.459	0.498
Paved shoulder indicator (1 if shoulder type is paved or paved with a warning device, 0 otherwise)	0.901	0.299	0.730	0.444
Poor pavement indicator (1 if pavement condition rating is below fair (i.e., PCI < 3), 0 otherwise)	0.172	0.378	0.272	0.445
FDOT District 1 indicator (1 if roadway segment is in District 1, 0 otherwise)	0.162	0.369	0.164	0.370
FDOT District 2 indicator (1 if roadway segment is in District 2, 0 otherwise)	0.279	0.448	0.258	0.437
FDOT District 3 indicator (1 if roadway segment is in District 3, 0 otherwise)	0.232	0.422	0.292	0.454
FDOT District 4 indicator (1 if roadway segment is in District 4, 0 otherwise)	0.025	0.156	0.029	0.167
FDOT District 5 indicator (1 if roadway segment is in District 5, 0 otherwise)	0.202	0.401	0.155	0.362
FDOT District 6 indicator (1 if roadway segment is in District 6, 0 otherwise)	0.043	0.203	0.031	0.173
FDOT District 7 indicator (1 if roadway segment is in District 7, 0 otherwise)	0.057	0.233	0.072	0.258

Table 4
Matched Case-Control Conditional Logistic Regression Model.

Variable	Parameter Estimate	t-Statistic	P > | z |	Odds Ratio (OR)	95% Confidence Interval of OR
Curve Characteristics					
Sharp non-reverse curve indicator	1.594	8.96	0.000	4.923	[3.474, 6.978]
Sharp reverse curve indicator	1.167	3.44	0.001	3.212	[1.652, 6.247]
Moderate reverse curve indicator	0.962	3.77	0.000	2.618	[1.587, 4.317]
Moderate non-reverse curve indicator	0.693	4.59	0.000	2.000	[1.458, 2.858]
Slight curve indicator	0.632	4.33	0.000	1.881	[1.412, 2.505]
Flat curve indicator	0.480	2.24	0.025	1.617	[1.063, 2.459]
Straight segment indicator	*Baseline*				
Roadway Characteristics					
Higher speed limit indicator	0.514	6.05	0.000	1.672	[1.416, 1.975]
Vertical slope indicator	0.365	4.20	0.000	1.441	[1.214, 1.710]
Auxiliary lane indicator	0.430	4.48	0.000	1.538	[1.273, 1.857]
Accessibility indicator	0.690	11.13	0.000	1.993	[1.765, 2.250]
Narrow surface width indicator	−0.537	−5.11	0.000	0.585	[0.476, 0.718]
Paved shoulder indicator	1.227	11.15	0.000	3.411	[2.750, 4.231]
Narrow shoulder width indicator	−0.214	−3.24	0.001	0.808	[0.710, 0.919]
Poor pavement indicator	−0.283	−3.45	0.001	0.754	[0.642, 0.885]
Geographical Characteristics					
FDOT District 3 indicator	−0.475	−5.46	0.000	0.622	[0.525, 0.737]
FDOT District 5 indicator	0.429	4.82	0.000	1.535	[1.289, 1.829]
FDOT District 6 indicator	1.312	6.80	0.000	3.713	[2.544, 5.419]
Other Districts	*Baseline*				
Model Statistics					
Number of observations	17,611				
Restricted log-likelihood	−3839.03				
Log-likelihood at convergence	−3373.10				
McFadden pseudo R-squared	0.121				

control data. Horizontal curve radius and curve type were combined into multiple dummy variables. Other explanatory variables, including roadway characteristics and geographical characteristics, were also evaluated in the model estimation process. The estimation results and 95% confidence interval of odds ratio are presented in Table 4. It is worth noting that pseudo R^2, used as the goodness-of-fit indicator in this study, cannot be interpreted independently or compared across datasets; the statistic is valid and useful only in comparing multiple

models predicting the same outcome based on the same dataset (Hox et al., 2017).

5. Empirical findings and discussions

5.1. Horizontal curve features

Horizontal curve features were expressed as a set of dummy

variables, including sharp reverse curve, sharp non-reverse curve, moderate reverse curve, moderate non-reverse curve, slight curve, and flat curve. The straight roadway segments were selected as the baseline for evaluating the effects of these horizontal curve features on single-motorcycle crash occurrence. As shown in Table 4, all coefficients for horizontal curve features are significant at a confidence level of 95%, and associated 95% CI of the odds ratios exclude 1, indicating that these CMFs are consistent at the 95% confidence level (Groos et al., 2010).

5.1.1. Radius of curvature

Odds ratios for horizontal curves (Table 4) decrease dramatically with the increase of horizontal curve radius, indicating that single-motorcycle crash risk on a curved segment decreases when its radius of curvature becomes larger. To be specific, the single-motorcycle crash risk on isolated sharp curves (radius ≤ 1500 ft), isolated moderate curves (1500 ft < radius ≤ 3000 ft), and isolated slight curves (3000 ft < radius ≤ 8000 ft) is 4.92 times, 2.00 times, and 1.88 times as high as that on straight segments (radius > 20,000 ft), because curve-related single-motorcycle crash risk factors such as speed variation (motorcycle speed difference between a curved segment and its adjacent straight segment), poor sight distance, and complexity of negotiation maneuvers would reduce significantly with the increase of horizontal curve radius. This finding is consistent with two previous studies (Schneider et al., 2010; Xin et al., 2017b).

The relationship between single-motorcycle crash risk and the radius of horizontal curvature is also validated with the curved sites. As shown in Fig. 2, the cumulative distributions of curved case sites and curved control sites by horizontal curve radius are compared. About 20% of horizontally-curved case sites are sharp curves, whereas only about 10% of horizontally-curved control sites are sharp curves. This finding indicates that single-motorcycle crashes are over-represented on sharp curves among all curved segments. In another study by the authors, sharp curves were also identified to increase the probability of severe injury in single-motorcycle crashes by 7.7% (Xin et al., 2017a).

5.1.2. Horizontal curve type

Horizontal curve types can be classified into reverse curve and non-reverse curve. As shown in Fig. 3, the effect of reverse design on single-motorcycle crash risk depends on the level of curve radius, which indicates the interaction effects between curve type and curve radius on single-motorcycle crash occurrence exist. To be specific, relative to non-reverse sharp curves, the reverse design of sharp curves leads to a dramatic decrease of single-motorcycle crash risk. This finding is perhaps because motorcycle riders become more alert and take safety-oriented measures (e.g., reducing speed at the entry of curve) to compensate for the difficulty of reverse-designed sharp curve negotiation. In
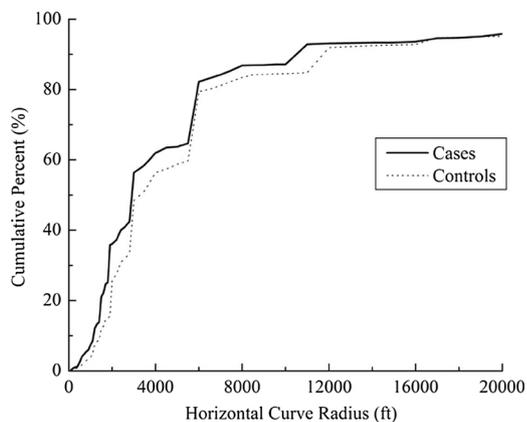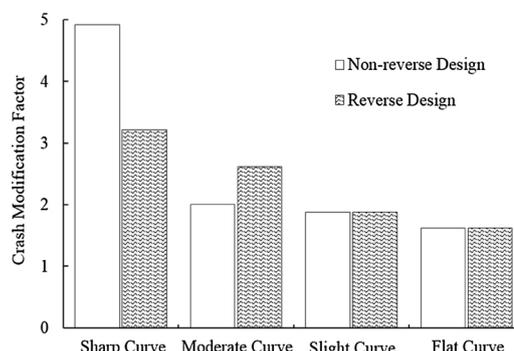

Fig. 3. Crash Modification Factors of Horizontal Curve Features on RTU Highways.

contrast, relative to non-reverse moderate curves, the reverse design of moderate curves is more likely to experience a higher relative risk in single-motorcycle crashes. A possible explanation is that on moderate curve segments, the increased risk by reverse-design-related maneuver complexity exceeds the reduced risk by reverse-design-related safety compensation behaviors. When the curve radius is greater than 3000 ft, the curve type has no significant effect on the risk of single-motorcycle crashes. This finding is because slight or flat curves (radius > 3000 ft) provide adequate sight distance and negotiation space for riders to counterweigh the risk of reverse design.

This finding is different from the previous study using the random parameter negative binomial model (Xin et al., 2017b), which concluded that the presence of reverse curve would decrease the single-motorcycle crash frequency by an average of 39%. The finding in this study is more reasonable than in previous studies because the previous models did not include the interaction item between curve type and curve radius. Also, reverse design was identified to increase the probability of severe injury in single-motorcycle crashes on horizontal curves by 5.8% (Xin et al., 2017a).

5.2. Roadway characteristics

A higher speed limit (> 50 mph) increases the risk of single-motorcycle crashes because maneuver complexity for motorcyclists increases with the traffic speed. The result supports the findings of earlier studies on the relationships between traffic speed and motorcycle crashes (Harnen et al., 2003; Machsus et al., 2013; Sharma et al., 2013). Single-motorcycle crash risk on RTU highways with a higher speed limit is 1.67 times as high as that on RTU highways with a lower speed limit.

The presence of auxiliary lanes and junctions on roadway segments increases the risk of motorcycle crash occurrence because the auxiliary lanes, which are linked to junctions, tend to increase the complexity of the traffic environment. Similar findings are reported in several previous studies (Abdul Manan et al., 2013; Machsus et al., 2013; Xin et al., 2017b). For example, Xin et al. (2017b) found that single-motorcycle crash frequency would increase with access density (i.e., number of junctions per mile).

The risk of motorcycle crash occurrence on roadway segments with vertical slope is significantly higher than that on roadway segments without a vertical slope. The presence of vertical slope could increase the complexity of motorcycle riding maneuvers by decreasing motorcycle rider sight distance. This finding is also in line with the authors' previous study (Xin et al., 2017b).

The odds ratios for narrow road surface width (< 24 ft) and narrow shoulder width (< 12 ft) are less than 1.0, indicating that single-motorcycle crash risk is lower on a narrow surface or narrow shoulder. This counterintuitive finding may have several possible reasons: (1)
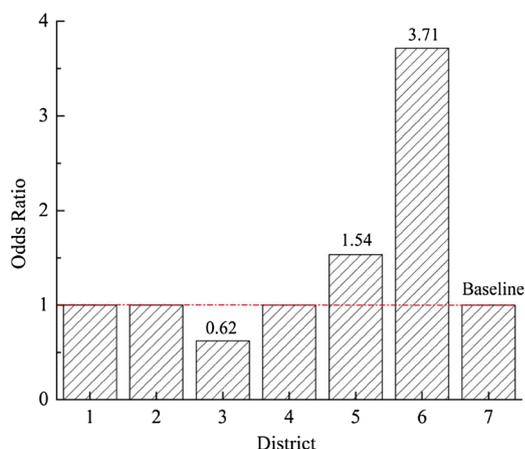

Fig. 2. Cumulative Distribution of Horizontally-Curved Segments by Curve Radius.

Fig. 4. Motorcycle Crash Risk on RTU Highways in FDOT Districts.

narrow surface and shoulder are usually installed on local roads and associated with low motorcycle exposure that tends to decrease single-motorcycle crashes; (2) local roads may be used mainly by local riders who are familiar with the roads and the curves; and (3) riders may respond to the relatively limited road surface width or shoulder width by increasing safety awareness and decreasing speed.

Paved shoulder type increases the probability of single-motorcycle crash occurrence dramatically, as motorcyclists may feel more confident and take risk-oriented behaviors (e.g., increasing speed and reducing alertness) on segments with paved shoulders compared to segments without paved shoulders. Also, paved shoulders are more likely to be set on RTU roads with heavy traffic volume and a high speed limit. The risk of a single-motorcycle crash on RTU highways with a paved shoulder is 3.04 times as high as that on highways without paved shoulders.

The matched case-control results indicate that a highway segment with poor pavement condition is expected to reduce single-motorcycle crashes relative to a highway segment with good pavement condition. In the authors' previous study (Xin et al., 2017a), poor pavement condition also was identified to reduce the injury severity of single-motorcycle crashes. This finding is because motorcycle riders who are aware of poor pavement conditions are more likely to take safety-compensation behaviors (e.g., reducing speed, increasing safety awareness).

5.3. Geographical characteristics

Geographical location (e.g., FDOT Districts) can be used as a proxy variable to reflect possible spatially-related unobserved factors in Florida, such as motorcycle population, weather characteristics, and demographic characteristics, which may influence both motorcycle exposure data and motorcyclist riding behaviors. As shown in Fig. 4, compared to the baseline (FDOT Districts 1, 2, 4, 7), FDOT Districts 5 and 6 experience relatively higher risks in single-motorcycle crashes (3.71 times and 1.54 times, respectively), and District 3 has a relatively lower risk of single-motorcycle crashes (0.62 times). FDOT District 5 (Orlando) and District 6 (Miami-Dade) are high-density population areas with more motorcycle exposures and are top-rated travel destinations, with many facilities to attract motorcyclist recreation activities (e.g., racing). Conversely, District 3 (in northwest Florida) has a low population density and, consequently, reduces the relative risk of single-motorcycle crashes.

6. Conclusions

This study explored the effects of horizontal curve design features (curve radius and curve type) on the risk of single-motorcycle crashes on RTU highways with a matched case-control study. The matched case-control study addressed the low sample-mean—the critical issue in cross-sectional studies of single-motorcycle crashes on RTU highways—by pre-specifying the number of cases (1601 in this study). Furthermore, the matched case-control study eliminated bias estimations caused by uncontrolled confounders (e.g., AADT, segment length) and aggregation observations over the years. The developed CMFs for horizontal curve features are all significant and consistent and can be used in *Highway Safety Manual*-compatible motorcycle safety management.

This study highlighted the interaction effects between horizontal curve types and radius on the risk of single-motorcycle crashes, which was not addressed in previous studies. Sharp non-reverse curves (radius ≤ 1500 ft) were identified as the riskiest curve design regarding single-motorcycle crashes for motorcycle riders, followed by sharp reverse curves and moderate reverse curves (1500 ft < radius ≤ 3000 ft). To reduce the risk associated with these curves, it is essential to ensure that riders are aware of the presence of sharp and reverse curves in advance to reduce initial entry speed. Advance warning devices advising riders of sharp and reverse curve presence, such as *Manual on Uniform Traffic Control Devices* advance warning signs, flashing beacons, and dynamic curve warning systems, are suggested for implementation on curves with a radius less than 3000 ft. Retroreflective delineation barriers and chevron signs can be installed to assist riders to comprehend curve sharpness and curve type in curve negotiation, especially with vertical slopes and/or in darkness.

Speed control is an effective countermeasure to decrease single motorcycle crashes on curves, especially on high speed limit (> 50 mph) curves. To avoid relative high-risk operating speed at the entry of curves, active speed warning signs and dynamic speed feedback signs are suggested to be installed on high speed limit (> 50 mph) curve segments or sharp-curve segments (radius < 1500 ft) of RTU highways.

This study revealed significant safety compensation effects for riders in negotiating curves. In addition to engineering countermeasures, a safety education program (e.g., training courses, education campaigns) is also an effective way to improve motorcyclist risk awareness (e.g., isolated sharp curve) and riding skills (e.g., proper cornering and breaking) in negotiating RTU curves.

A limitation of this study is spatial correlation. Although an FDOT District indicator was included in the conditional logistic model to address unobserved spatial factors, the resolution of the spatial indicator is too low to capture "true" heterogeneities. For example, motorcycle exposures were usually unknown and assumed to be proportional to AADT in previous studies. However, motorcycle traffic often varies over rural highways even when they have similar AADT (e.g., some trails in Florida are more attractive to motorcycle riders for recreation). Matching by AADT and multivariate fitting of Districts cannot capture the difference of motorcycle exposures over cases and controls. A possible solution in the future study is to match cases with controls by relative spatial location (e.g., along with the same rural road segment) to address the heterogeneity effects of spatial-related unobserved factors (e.g., motorcycle exposure, riding behaviors, and weather condition).

Acknowledgments

Appendix A

Table A1

Descriptive Statistics of Collected Variables for Curved Segments.[a]

Variable Description	Mean	Std.	Min.	Max.
Single-motorcycle crash frequency (per year)	0.02	0.13	0	3
Curve radius (ft)	7,104	25,167	93	686,452
Segment length (ft)	1,821	1,155	612	32,039
Speed limit (mph)	54.36	6.79	25	70
Surface width of through lanes (ft)	23.59	1.34	18	48
Shoulder type (1 if paved shoulder, 0 if not)	0.85	0.36	0	1
Shoulder width (ft)	11.25	3.06	2	24
Grade indicator (1 if a vertical slope exists, 0 if not)	0.10	0.30	0	1
Number of auxiliary lanes	0.10	0.46	0	8
Number of access points within segment	0.91	1.33	0	14
Pavement condition (0.0 – very poor to 5.0 – very good)	3.76	0.61	0	5
AADT	4,102	3,047	100	35,000

[a] 26,884 observations = 2444 sites × 11 years.

Table A2

Descriptive Statistics of Collected Variables for Straight Segments.[b]

Variable Description	Mean	Std.	Min.	Max.
Single-motorcycle crash frequency (per year)	0.01	0.11	0	4
Segment length (ft)	3,731	2,993	602	30,540
Speed limit (mph)	50.44	9.19	15	70
Surface width of through lanes (ft)	22.67	2.13	18	48
Shoulder type (1 if paved shoulder, 0 if not)	0.53	0.50	0	1
Shoulder width (ft)	9.90	3.63	1	36
Grade indicator (1 if a vertical slope exists, 0 if not)	0.07	0.26	0	1
Number of auxiliary lanes	0.08	0.48	0	22
Number of access points	1.44	1.98	0	33
Pavement condition (0.0 – very poor to 5.0 – very good)	3.54	0.67	0	5
AADT	3,479	3,172	10	57,000

[b] 111,804 observations = 10,164 sites × 11 years.

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