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A Penalized-likelihood Approach to Characterizing Bridge-related Crashes in New Jersey

--Manuscript Draft--

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ABSTRACT

A roadway departure crash is one in which a vehicle crosses an edge line, a centerline, or otherwise leaves the traveled way. These crashes that involve run-off-road and cross-median/centerline head-on collisions tend to be more severe than other crash types. According to the NHTSA Fatality Analysis Reporting System database, a total of 7,833 people perished in crashes involving fixed roadside objects in 2017, accounting for 21 percent of the total number of fatalities in the United States. Several previous studies have reported that rural bridge-related crashes result in more fatalities due to their being mostly the fixed-object crash type. As such, further in-depth investigation of this type of crash is necessary. Due to the lack of a comprehensive database that includes bridge-related crashes and bridge characteristics, identifying the key factors contributing to this type of crash is a challenging task that is addressed in this paper. We gathered and compiled five years of crash data from the New Jersey crash database and the characteristics of bridges from the Long-Term Bridge Performance portal. A Firth's penalized-likelihood logistic regression model was developed to examine the influence of explanatory variables on crash severity. This model is an appropriate tool for controlling the influence of all the confounding variables on the probability of bridge-related crashes while also considering the rareness of the event. Based on the obtained odds ratio, the various effects of the identified variables are discussed and recommendations made regarding countermeasures policymakers can establish to reduce the number of these crashes in New Jersey.

Keywords: Bridge-related crash, Fixed-object, Odds ratio, Firth's logistic model

INTRODUCTION

A roadway departure crash is defined by the Federal Highway Administration (FHWA) as "a crash in which a vehicle crosses an edge line, a centerline, or otherwise leaves the traveled way" *(1)*. These crashes, which involve run-off-road and cross-median/centerline head-on collisions, tend to be more severe than other crash types *(2)*. According to the FHWA, between 2015 and 2017, an average of 52 percent of motor vehicle traffic fatalities occurred each year due to roadway departure crashes (*1*). Moreover, a total of 7,833 people died in fixed-object crashes (e.g., trees, bridge pier, traffic barriers, and guardrail ends) in 2017, accounting for 21 percent of the total fatalities in the United States *(3)*. Several previous studies (*2, and 4*) have reported that bridge-related crashes result in more fatalities due to their being mostly the fixed-object crash type. As such, further in-depth investigation of this type of crash is necessary.

Bridges are an important component of the U.S. highway system (*5, and 6*). According to the FHWA's Long-Term Bridge Performance (LTBP) program, there are more than 611,000 bridges across the U.S. It should be noted that the physical and operational characteristics of bridges differ significantly from those of roads and highways (*6, and 7*). Specifically, the traffic lanes on bridges are usually narrower than the approach roads and usually lack shoulders that can safely accommodate vehicles and provide drivers with more space to maneuver and avoid crashes. Notably, bridges have different components such as railings, piers, surface wear, and guardrails that can cause safety hazards to vehicles traveling on or under them. Therefore, bridge-related characteristics significantly affect the safety of traffic traveling along and near bridges (*6*).

Over the past years, several studies have focused on identifying the major contributing factors to bridge-related crashes. Turner (1984) analyzed four years of Texas crash data and found that narrow bridges were associated with higher crash rates *(8)*. In another study, Ranes and Guro (2000) explored the crash rates associated with 758 bridges in Norway. The results of that study indicated that the width, length, and age of the bridges and the average annual daily traffic (AADT) contributed significantly to bridge-related crashes *(9)*. In a recent study, Elvik et al. (2019) developed a negative binomial regression model to analyze seven years of data (2010–2016) on crashes that had occurred in or around 6,824 road bridges in Norway. The authors of the study found that traffic volume significantly contributed to the likelihood of bridge crashes *(10)*. The results of a study conducted by Khan et al. (2009) revealed that surface conditions (ice with a lower coefficient of friction) greatly contributed to the frequency of bridge crashes *(11)*. Mehta et al. (2015) developed safety performance functions to estimate the expected number of crashes on bridges in Alabama. The results of that study demonstrated that bridge length, percentage of trucks, and AADT contributed significantly to bridge-related crashes *(6)*. Buth et al. (2010) investigated data from 32,934 large-vehicle/fixed-object crashes in which the vehicle had hit a bridge structure. The results showed that lane width, bridge density, and bridge width were all significantly associated with the bridge crashes *(12)*. Schrock et al. (2012) explored the association between pavement conditions, roadway geometry, and large trucks in fixed-object crashes over bridges. The authors concluded that the injury severities associated with fixed-object crashes that involved bridges (e.g., bridge rails, headwalls, piers, abutments, or guardrails) were 4.93 times higher than those associated with limited access facilities *(13)*.

Despite the several bridge-related crash studies reported in the literature *(6, 8-13)* very few have identified and compared the factors affecting the injury severity of bridge-related cashes. Due to the very limited relative number of bridge-related crashes and the lack of a comprehensive database that includes bridge-related crashes and bridge characteristics, identifying the key factors contributing to this type of crash is a challenging task, which we address in this paper. A Firth's penalized-likelihood logistic regression was developed to characterize bridge-related crashes. This model is an appropriate tool for controlling the influence of all the confounding variables on the severity of bridge-related crashes while also considering the rareness of the event.

METHODS

Firth's Penalized-likelihood Logistic Regression

Based on the compiled data, three conditions were identified in relation to bridge-related crashes, including the rarity phenomenon, unbalanced data, and disproportionality of explanatory variables. The observed crash frequency results indicate that vehicular crashes involving bridges are very rare events; consequently the sample size is very small. Second, some categories for bridge-related crashes have very low frequency, which can cause computational problems *(14)*. Third, statistical guidelines recommend having at least 10 observations per each explanatory variable to construct an effective model and calculate the parameter estimates *(15)*. These issues can limit the applicability of standard logistic regression since it uses maximum likelihood estimation (MLE), which suffers from small-sample bias. In this situation, a penalized-likelihood approach (i.e., Firth's logistic regression) is suggested, which can avoid the shortcomings of MLE *(16, and 17)*.

Firth's penalized-likelihood logistic regression model is a generalization of MLE models that can effectively avoid the bias that otherwise arises in calculations due to the small sample size and rareness of the event (which is the case in this study). We note that Firth's penalized-likelihood logistic regression model has specifically been employed in the medical sciences. For instance, Mulla et al. (2012) investigated a sample of 138 patients, only 16 of which were diagnosed with preeclampsia, for which computational problems would have arisen in an analysis using MLE methods *(18)*. Xu et al. (2012) examined a sample size of 67 patients, only 28 of whom had developed hypertension, which is a very small sample size if using the MLE method. Considering the type of dependent variable in this study (injury crashes vs. property-damage-only crashes), a binary logistic regression is recommended *(19)*.

Firth introduced a penalized MLE into the binary model that can counteract the bias associated with MLE *(16)*. The log-likelihood can be expressed as an exponential family model as follows:

$$(\beta)=t\beta_n-(\beta_n),\ n=1,\ldots,k \qquad (1)$$

where β_n is the regression parameter to be estimated, t is the vector of the observed sufficient statistics, and k is the number of parameters estimated. The derivative of the log-likelihood, the score function, is employed to calculate the MLE of parameter β_n as follows:

$$(\beta_n)=l'(\beta_n)=t-K(\beta_n),\ n=1,\ldots,k. \qquad (2)$$

To penalize the MLE, Firth replaced the score function of the binary model with a modified score function as follows:

$$(\beta_n)^{*}=(\beta_n)+\alpha_n,\ n=1,\ldots,k \qquad (3)$$

where α_n has the n^{th} entry, which is represented as:

$$\alpha_n = 1/2\ tr[(\beta)^{-1}\ \partial I(\beta)/\beta_n],\ n=1,\ldots,k \qquad (4)$$

Where *tr* is the trace function and (β) is the Fisher's information matrix. Using this method, the MLE drops to zero. For small samples, Firth's method is more accurate in estimating coefficients and evaluating confidence intervals with respect to coverage probabilities, as compared to the performances of the broad class of generalized linear models *(20)*. After calculating the parameter estimates for statistically significant variables, the odds ratio (OR) was calculated as a relative measure of the effect. The OR can be used to better understand the direction and magnitude of the change in the probability of the dependent variable with a one unit change in the specific variable. That is, when the OR is greater than one, the study group (here, injury crashes) is more likely to have the specific characteristic, as defined in the category, than is the reference category. A similar explanation applies to an OR less than one.

DATA

In this study, the required data for analysis were obtained from two primary sources: the New Jersey Crash Database and Long-Term Bridge Performance (LTBP) portal. Unlike other crash types that require only the development of specific filters to prepare the final dataset for analysis, bridge-related crashes require some extra steps prior to analysis to ensure that the dataset has the highest possible accuracy. Specifically, possible bridge-related crashes were identified by defining several filters and then additional steps were taken to verify the actual occurrence of these crashes. The first filter phase produced several crashes that had not actually occurred on bridges. For example, by considering the vehicle direction, travel crashes that occurred along a bridge underpass were excluded from further analysis. Visual inspection using Google Street View and Microsoft's Bird's Eye view were used to verify the locations of crashes. After filtering out non-bridge-related crashes via the above-mentioned steps, our final dataset included 284 single-vehicle, run-off-road crashes involving vehicles striking a bridge-related component that had occurred on 116 public bridges in Middlesex County, New Jersey from 2011 to 2015.

Information regarding the bridge characteristics (i.e., surface wear, bridge railing, guardrail end, bridge roadway width, bridge length, left and right curb/sidewalk widths, median type, and average daily traffic) was obtained from the LTBP portal. This portal includes a variety of information related to the historical conditions and traffic data of bridges from 1992–2016, environmental data such as the number of snowfalls and freeze–thaw cycles, a field-testing database of 80 bridges, and legacy information *(21)*. The LTBP portal is a web-based platform developed by a FHWA LTBP program that collected all data related to bridge performance. Table 1 lists the explanatory variables along with their percentages used in this study. When looking at this table, a few points are worthy of mention. For example, almost 40% of bridge-related crashes during this period occurred during evening and night hours. Moreover, approximately 60% of bridge-related crashes occurred during autumn and winter and 94% of the drivers had not been impaired.

TABLE 1 Description of Explanatory Variables

Variable	Frequency	Percentage
Driver Characteristics		
Age		
Younger Drivers (Less than 24)	97	34.20%
Middle-aged drivers (25 to 64)	164	57.70%
Older drivers (65 and over)	17	6.00%
Unknown	7	2.30%
Gender		
Male	187	65.80%
Female	97	34.20%
DUI Driving?		
Yes	16	5.60%
No	268	94.40%
Temporal Variables		
Season		
Spring	67	23.60%
Summer	52	18.30%
Autumn	77	27.10%
Winter	88	31.00%
Day of Week		
Weekday	189	66.50%
Weekend	95	33.50%
Time of Day		
Morning	77	27.10%
Afternoon	96	33.80%
Evening	57	20.10%
Night	54	19.00%
Crash Variables		
Injury Severity		
Injury	75	26.40%
PDO	209	73.60%
Weather Condition		
Clear	164	57.70%
Adverse	120	42.30%
Surface Condition		
Dry	149	52.50%
Wet	135	47.50%
Lighting Condition		
Daylight	161	56.70%
Dawn/Dusk	16	5.60%
Dark-Lit	79	27.80%
Dark- not lit	28	9.90%
Roadway Characteristic		
Straight	169	49.50%
Curve	115	40.50%
Direction of Traffic		
One way	128	45.10%
Two way	156	54.90%
Speed Limit		
Less than 25 mph	28	9.90%
26 to 35 mph	69	24.30%
36 to 45 mph	0	0.00%
46 to 55 mph	130	45.80%
More than 56 mph	57	20.10%

1 **TABLE 1 Description of Explanatory Variable (Cont.)**

Variable	Frequency	Percentage
Vehicle Characteristics		
Vehicle Age		
Less than 5 years	75	26.40%
5 to 14 years	179	63.00%
More than 15 years	28	9.90%
Bridge Characteristics		
Wearing Surface		
Monolithic Concrete	116	40.80%
Integral Concrete	4	1.40%
Latex Concrete	35	12.30%
Bituminous	110	38.70%
None	19	
Bridge Railing		
Meet acceptable standard	93	32.70%
Does not meet standard	191	67.30%
Approach Guardrail End		
Meet acceptable standard	221	77.80%
Does not meet standard	63	22.20%
Median Type		
Barrier Median	170	59.90%
Curbed Median	25	8.80%
Grass Median	21	7.40%
Painted Median	8	2.80%
None	58	20.40%
Other	2	0.70%

2

Variable	Min	Mean	Max
Continues Variables			
Ln ADT	5.6	10.5	12.3
Bridge Roadway Width	6.6	22.1	66.4
Length	6.1	62.8	479.1
Left Curb/Sidewalk Width	0	0.7	3.7
Right Curb/Sidewalk Width	0	0.7	4.3

RESULTS AND DISCUSSION

As previously discussed, for the purpose of this study, Firth's model was found to be more suitable than an MLE model for the analysis of the study variables. To estimate the effect of various confounding factors contributing to the probability of bridge-related crashes, the R software package "logistf" was employed *(*22*)*. First, a model was fit with all the possible contributing factors and then a backward elimination procedure was adopted, based on the penalized-likelihood ratio test, to identify a model that best agreed with the crash data. A forward selection process produced a similar result. Table 2 shows a summary of the results of the Firth's model, including parameter estimates and their corresponding standard errors and ORs. All of the estimated parameters included in the model are statistically significant at the 95 percent confidence interval.

TABLE 2 Firth's Model Results

Explanatory Variable	Firth's Model		OR (odds ratio)
	β	S.E.	
Time of Day			
Morning (6:00-12:00)	Reference		
Afternoon (12:00-18:00)	-0.792	0.187	0.453
Driver Gender			
Female	Reference		
Male	0.516	0.548	1.675
Weather Conditions			
Adverse	Reference		
Clear	0.780	1.07	2.181
Surface Conditions			
Wet	Reference		
Dry	-0.942	0.196	0.39
Speed Limit			
Less than 25mph	Reference		
26mph to 35mph	-0.837	0.251	0.433
Direction of Traffic			
Two-way	Reference		
One way	0.947	1.588	2.577
Lighting Condition			
Daylight	Reference		
Dark-not Light	-1.309	0.229	0.27
Roadway Characteristic			
Curve	Reference		
Straight	-1.036	0.454	0.355

In this study, considering the lighting conditions, the time of day was categorized into four categories including morning (6:00–12:00), afternoon (12:00–18:00), evening (18:00–24:00), and night (0:00–6:00). In Table 1, evening and night periods account for about 60% of the total number of bridge-related crashes. The results of the analysis indicate that bridge-related crashes during the afternoon were 0.45 times less likely to involve injuries compared with those in the morning. This result is in a good agreement with a number of other studies *(23)*.

With respect to gender, male drivers (65.8 percent) experienced more bridge-related crashes than female drivers (34.2 percent), which means that male drivers were 1.67 times more likely to be involved in injury-related crashes than females. A number of reasons might explain this finding. For example, males drive more miles than women and tend to use more risky behaviors such as driving under the influence of alcohol or drugs and speeding, which results in more severe crashes *(24-26)*. Moreover, male drivers have a greater exposure to potential crashes due to the relatively higher number of licensed drivers and greater annual vehicle miles traveled (*27*).

According to the estimation results presented in Table 2, weather conditions significantly contributed to the injury severity associated with bridge-related crashes. Specifically, bridge-related crashes in clear weather condition were 2.18 times more likely to be injury-related crashes. This finding is also in a good agreement with those reported by Christoforu et al. (2010) and Jalayer et al. (2018), which indicates that drivers are more likely to be vigilant regarding their surroundings during adverse weather conditions, which mitigates the severity of injuries *(28, and 29)*.

Similar to weather conditions, the surface condition was also found to significantly contribute to the injury severity of bridge-related crashes. Compared to dry surface conditions, wet surface conditions contributed significantly to the severity of injuries. Specifically, bridge-related crashes in dry surface conditions were 39 percent less likely to result in severe injury. Again, this finding is consistent with other research results *(30)*.

In this study, the speed limit was divided into five categories, including less than 25 mph, 26–35 mph, 36–45 mph, 46–55 mph, and faster than 56 mph. The speed-related results show that bridge-related crashes that occurred at speed limits between 26 mph and 35 mph were 0.43 times less likely to result in injuries compared to those that happened at speed limits below 25 mph. No specific reasons were found to explain this phenomenon. Further studies and more data are needed to determine whether this trend persists over a longer time period.

When comparing injury and property-damage-only bridge-related crashes, the direction of traffic was found to be a statistically significant factor. As shown in Table 2, bridge-related crashes that occurred in one-way traffic were 2.57 times more likely to have injuries than those with two-way traffic.

Lighting conditions also played a significant role in the injury severity of bridge-related crashes. In this study, lighting conditions were classified into four categories: daylight, dawn/dusk, dark-lit, and dark-not lit. Based on the compiled data, more than 50 percent of the bridge-related crashes occurred during daylight. It should be noted that darkness, when there is no lighting provided, decreases the severity of crashes (27 percent decrease in the injury crashes) compared to those in daylight conditions. Several factors might explain this finding. For instance, in dark conditions, drivers tend to engage in more risk-compensating behaviors (e.g., driving at lower speeds, paying more attention to the surroundings), which results in crashes with less severe outcomes *(31)*.

With regard to roadway characteristics, bridge-related crashes that happen on straight road segments are 0.35 times less likely to produce injuries than those that happen along curves.

Moreover, based on the obtained results, an increase in bridge road width reduces the likelihood of injury crashes (OR=0.95). Roadway curvatures are known to reduce available sight distance and decrease vehicle-control capabilities, which increase the probabilities of crashes and injuries *(2)*.

CONCLUSIONS

In this study, significant factors were identified that affect the severity of bridge-related crashes based on five years (2011–2015) of crash data in Middlesex County, New Jersey. Given the rareness of bridge-related crashes, Firth's penalized-likelihood logistic regression model was employed and the corresponding OR were calculated to measure the relative effect of significant variables. The results of the analysis demonstrated that a variety of factors significantly contributed to injury severity. The results from the best-fitted model indicate that bridge-related injury crashes were more likely to involve a male driver (OR = 1.67) and to occur in clear weather conditions (OR = 2.18), on one-way roads (OR = 2.57), and on bridges with narrow widths (OR = 0.95). Similarly, bridge-related injury crashes were less likely to occur in dry surface conditions (OR = 0.39), on straight roads (OR = 0.35), in dark lighting conditions (OR = 0.27), in the afternoon (OR = 0.45), and on facilities with speed limits between 26 mph and 35 mph (OR = 0.43).

Based on the findings obtained in this study, specifically the obtained ORs, several countermeasures and recommendations can be suggested to reduce the occurrence of this type of crash. Behavior-based countermeasures should target male drivers in particular, given that this driver group was significantly overrepresented by higher OR values. Engineering countermeasures can focus on increasing bridge widths or approach widths. Guiderail upgrades and signage and lighting enhancements are also recommended limitations. This study is not without limitations. For example, the data used in this study were from just one county in New Jersey. Incorporating more data from other counties and states would not only bolster the sample size but might also lead to a more comprehensive result that could facilitate the development of better countermeasures and strategies. Another limitation of this study is the inevitable role of human error in the data collection process by police officers, which affects the level of detail and accuracy of the obtained significant variables.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Jalayer and Parvardeh; data collection: Jalayer, Parvardeh, and Patel; analysis and interpretation of results: Pour-Rouholamin and Jalayer; draft manuscript preparation: Patel, Jalayer, and Das. All authors reviewed the results and approved the final version of the manuscript.

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