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Crash Frequency Analysis of Left-side Merging and Diverging Areas on Urban Freeway Segments: A Case Study of I-75 through Downtown Dayton, Ohio

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ABSTRACT

This paper analyzes the effect of left- and right-side merging and diverging areas and other variables such as light condition, roadway pavement condition, drivers' age and presence of construction work zones on the occurrence frequency of crashes. A 6.5-mile (10.5-km) section of I-75 that passes through downtown Dayton, Ohio was considered.The area of interest has a high traffic volume and consists of different geometric design challenges including closely spaced merging and diverging ramps. A four-year record of crash data (2005-2008) and a statistical modeling technique that assumes a negative binomial distribution on generalized linear models (GLMs) were used to develop separate models for merging and diverging areas. The model results show that left-side merging and diverging areas are critical elements in crash frequency in the vicinity of ramps on freeways. In addition, pavement condition, light condition, and work zones were found to be significant predictors of crash frequency. Specifically, the results indicate that crashes are about 7.88 times more likely to occur on merging areas located on the left side of the freeway lanes compared to those on the right. For diverging areas, about 2.26 times more crashes are likely to occur near diverging areas on the left compared to those diverging on the right side of the freeway. In addition, adverse pavement conditions (such as wet pavement, snow, and ice), adverse light conditions (such as darkness and glare), and presence of work zone were found to be significant variables in the occurrence of crashes.

Keywords: Crash Frequency, Negative Binomial, Generalized Linear Model, Merging Areas, Diverging Areas.

1. Introduction

Traffic crashes occurring on transportation facilities continue to be major socio-economic concerns due to the large number of lives, bodily injuries and loss of property claimed by these crashes. Consequently, transportation agencies are exerting considerable amount of effort and resources to improve these facilities as countermeasures in an attempt to alleviate these losses. The causes of traffic crashes can be categorized into classes of variables such as geometric design elements, human/driver-related factors, traffic and environmental factors. The arrangement of lanes and ramps in urban freeways at merging and diverging areas are important geometric factors for safe and efficient use of these facilities. Due to considerably greater demand for access to freeways as they pass through urban central business areas (CBDs) and the limited right-of-way available compared to suburban and rural areas, configurations of on- and off-ramps are sometimes erratically provided both on the left- and right-sides of the mainline freeway lanes in order to make them as accessible as possible.

Therefore, this paper explores the effects of geometric characteristics by comparing the location of left-side ramps versus right-side ramps by developing two separate models for merging and diverging areas. In addition, other factors such as driver's age, traffic volume on mainlines, environmental factors (i.e., roadway pavement conditions, lighting conditions, weather conditions), and presence of construction work zones at the time of crash were also explored. For this study, the negative binomial distribution was used to predict the effect of these variables on crash frequency.

A number of efforts have studied and modeled safety issues and factors affecting crash frequency in the vicinity of freeway junctions over the past several years. Because left-side junctions are generally rare, most of these studies have concentrated with the more typical, the right side junctions. A study by Bauer and Harwood (1998) indicated that ramp annual average daily traffic (AADT), area type, ramp type, ramp configuration, and ramp length to be significant factors affecting crash frequency. Bared et al. (1999) evaluated the safety effects of acceleration and deceleration lanes and found that off-ramps (on diverging areas) were more prone to traffic crashes than on-ramps (on merging areas) and the crash frequency at ramps is affected by freeway's AADT.

McCartt et al. (2004) studied crashes that occurred on urban interstate ramps in northern Virginia. Most of the crashes (about 50%) occurred at exit (off) ramps and they were mostly run-off road type of crashes. Several studies (Chen et al., 2009; Chen and Lu, 2009; Pan et al., 2010) evaluated the safety impacts of arrangement and number of lanes on freeways on diverging areas in Florida. Mergia et al. (2013) explored factors contributing to injury severity at freeway merging and diverging areas in Ohio by developing separate models for merging and diverging areas. However, it is noteworthy to mention that so far all of the above discussed studies did not consider left-side merging and diverging areas. Studies by Zhou et al. (2010), Zhao and Zhou (2011) and Chen et al. (2011) studied safety and operational effects of left-side exits at freeway diverging areas in Florida. All these Florida studies conclude that left-side diverging areas have higher crash frequency as compared to those located on the right side of the mainlines. It is regrettable that these studies did not include merging areas.

Since left-side junctions are not as common as right-side junctions on most freeways, their impacts on freeway safety have not been adequately studied. The studies by Zhou et al. (2010), Zhao and Zhou (2011) and Chen et al. (2011) evaluated the effect of diverging areas only as mentioned above and the junctions studied are located over a relatively larger geographical area. Therefore, a study of the occurrence frequency of crashes at left-side and right-side junctions in urban areas of relatively higher ramp/junction density and a comparison thereof would be of paramount significance in the management, planning and safe and efficient operation of urban freeways. Accordingly, the present study utilized a short section, 6.5 miles (10.5 km) long of Interstate 75 that passes through downtown Dayton that includes interchanges at US-35, SR 4 and SR 48, which have been named among the nation's malfunctioning junctions due to the high number of traffic crashes occurring on this short stretch of I-75. This section is characterized by uncommon geometric designs such as left side on- and off-ramps, weaving sections, and varying number of lanes.

2. Methodology

Crash frequency modeling involves counting crashes that are related to a certain specific set of explanatory variables of interest. Therefore, crash frequency data is basically a count data that is commonly modeled assuming Poisson and negative binomial distributions (Shankar et al., 1995; Milton and Mannering, 1998; Chang, 2005; Lord et al., 2005; Xie and Zhang, 2008; Lee and Abdel-Aty, 2009; Moon and Hummer, 2009; Liu et al., 2010).

A unique characteristic of the Poisson distribution is the assumption of equality between the mean and variance of the expected number of crashes. However, there are many instances where this assumption may not be valid for traffic crash count data (Lord et al., 2005; Hauer, 2001). Due to this limitation, model prediction using the Poisson distribution could lead to biased and erroneous parameter estimates and hence incorrect inferences. As a result, for an over-dispersed crash data the negative binomial distribution becomes a better choice (Poch and Mannering, 1996; Hauer, 2002). The probability distribution for the negative binomial is modeled as shown in Equations 1 through 4 (Simonoff, 2003):

$$f(Y_i : \mu_i, \nu) = \frac{\Gamma(Y_i + \nu)}{Y_i!\Gamma(\nu)} \left(\frac{\nu}{\nu + \mu_i} \right)^{\nu} \left(\frac{\mu_i}{\nu + \mu_i} \right)^{Y_i} \quad (1)$$

$$\mu_i = E(Y_i) = \exp(\beta X_i) \quad (2)$$

$$Var(Y_i) = \mu_i (1 + \alpha \mu_i) \quad (3)$$

$$\alpha = 1/\nu \quad (4)$$

Where:

β and α = coefficients estimated using maximum likelihood techniques
Γ = Gamma function,
Y_i = the observation *i*; *i* = 1,..., n
μ_i = the expected value (mean) of observation *i*
$Var(Y_i)$ = the variance of the random variable Y_i
ν = inverse of the dispersion parameter.

Generalized linear models can be derived from classical linear models. Equation 5 represents a classical linear model (Sloboda, 2009):

$$\eta_i = \beta_0 X_{i0} + \beta_1 X_{i1} + \ldots + \beta_j X_{ij} + \ldots + \beta_{p-1} X_{ip-1} = \sum_j \beta_j X_{ij} \quad (5)$$

Where:

For *i* = 1, …, n, and *j* = 0, 1, …, p-1
X_{ij} = the value of explanatory variable *j* for observation *i*
β_j = the parameter determining the direction and degree of association of μ_i with explanatory variable X_{ij}

A generalized linear model can be represented by Equation 6:

$$\eta_i = \beta_0 + \beta_1 x_{1i} + \ldots + \beta_j x_{ij} \quad (6)$$

In this study a log link that relates η_i to the mean of Y_i was used and it is represented as shown in Equation 7:

$$\eta_i = \log(\mu_i) \quad (7)$$

The combination of Equations 6 and 7 leads to Equation 8, which represents the functional form that relates the logarithm of expected traffic crash frequency with explanatory variables.

$$\eta_i = \log(\mu_i) = \beta_0 + \sum_{j=1}^{n} \beta_j x_{ij} \tag{8}$$

or

$$\mu_i = \exp\left\{\beta_0 + \sum_{j=1}^{n} \beta_j x_{ij}\right\} \tag{9}$$

Where the variables are as defined above.

2.1 Study site

The study area is a 6.5 miles (10.5 km) stretch of Interstate 75 between Edwin C Moses Boulevard and Needmore Road interchanges as it passes through downtown Dayton, Ohio. Interstate 75 enters Ohio from Kentucky and continues north to Michigan and it is considered one of the most important interstate highways in the state of Ohio. The area of interest has a high traffic volume and it consists of different geometric design challenges including merging and diverging ramps which are closely located. Additionally, some of these ramps are located on the left side of the travel movements. The number of lanes in one direction varies between two and four within the study area, which forces some of the drivers to be involved in a number of weaving maneuvers as some previously through lanes get dropped as they become exit paths.

2.2 Data collection and preparation

Crash data were obtained from Ohio Department of Public Safety (ODPS) crash database for years 2005-2008. ODPS maintains all police-reported traffic crashes that occur on public roads in the state of Ohio. All other crash-related variables of interest in this study such as weather condition, light condition, driver’s age, and presence of construction work zones are always included as part of crash recording and are easily extracted from the ODPS database. The exact locations of where traffic crashes occurred were determined by using the longitude and latitude information obtained from the crash database. Therefore, by using longitude and latitude data, a GIS shape file was created containing crash information and it was then converted into a keyhole markup language (kml) file format in order to display the crash locations on a Google Earth map. This helps to accurately display each crash event on a particular roadway point on Google Earth map which in turn helps to identify its geometric attributes. Consequently, each traffic crash data was linked accurately to its corresponding roadway geometric attributes. The traffic crash data were then categorized according to the location of freeway and main junction type where they occurred: (1) merging crash data and (2) diverging crash data.

With the exception of AADT, all other factors are categorical variables. Traffic volume counts (AADT) were obtained from Ohio Department of Transportation (ODOT) database. Weather condition, light condition, and road condition were decoded into binary variables (mainly because some of the samples were very small and had to be combined with others) as shown in Table 1. Each crash data was reviewed and coded as shown in Table 2. Moreover, Table 2 shows the frequency of crashes categorized as merging and diverging data.

Table 1
Decoding of weather, light, and roadway conditions

Variable	Code	Variable Description
Weather Condition	1 = adverse	Fog, smoke, smog, rain, sleet, hail, snow, and severe crosswinds
	2 = normal	Clear and cloudy
Light Condition	1 = adverse	dark, and glare
	2 = normal	Daylight and dawn
Road Condition	1 = adverse	Wet, snow, and ice
	2 = normal	Dry

Table 2
Independent variables considered in this study

Variable	Description	Code	Variable Type	Number of Traffic Crashes	
				Merging Areas	Diverging Areas
VC	Volume Count (AADT)	In 1000's of vehicles	Continuous		
WC	Weather Condition	1 = Adverse	Class	202	172
		2 = Normal		519	632
LTC	Light Condition	1 = Adverse	Class	191	172
		2 = Normal		530	632
RC	Road Condition	1 = Adverse	Class	237	213
		2 = Normal		484	591
Age	Driver's age	1 = < 21 years	Class	132	142
		2 = $\geq$ 65 years		39	51
		3 = 21-64 years		550	611
WZ	Work Zone	1 = Yes	Class	88	112
		2 = No		633	692
BD	Bridge	1 = Yes	Class	459	529
		2 = No		262	275
MG	Merging	1 = merging left	Class	58	--
		2 = merging right		663	--
DV	Diverging	1 = diverging left	Class	--	220
		2 = diverging right		--	584
Total				721	804

A total of 721 merging and 804 diverging traffic-related crashes that occurred within the study area in the period between January 2005 and December 2008 were used in this study. Table 3 provides a descriptive statistical summary comparing merging and diverging crash data.

Since variances of both datasets are much larger than their corresponding means, the data can be termed as overdispersed. However, according to Xie and Zhang (2008), we cannot sufficiently conclude from these results that overdispersion exists because the variation of various parameters used in this study can affect the overall variance and mean. A statistical test performed to confirm the overdispersion in the data is discussed in the next section.

Table 3
Statistical summaries of merging and diverging crash data

Parameter	Crash Frequency for Merging	Crash Frequency for Diverging
Mean	4.05	4.25
Minimum	1.00	1.00
Maximum	28.00	30.00
Variance	38.52	40.54
Std. Dev.	6.21	6.37

2.3 Model goodness-of-fit and overdispersion tests

If the over-dispersion in the data is not captured in the analysis it results into underestimation of standard errors and hence over-statement of significance in hypothesis testing (Pedan, 2001). Consequently, using an inappropriate model for count data can grossly affect the statistical inference and the resulting conclusions. Deviance (D) and Pearson Chi-Square statistic (χ^2) divided by the degrees of freedom (DF) are used to detect whether overdispersion or underdispersion exists in the data and also can be used to indicate other problems such as incorrectly specified model or presence of outliers in the data (SAS, 2004). Evidence of either overdispersion or underdispersion indicates inadequate fit of the Poisson model. The goodness of fit between the observed data and the estimated values from a Poisson distribution or a negative binomial distribution are usually measured by using the log-likelihood ratio statistic (i.e., the deviance) and the Pearson chi-square χ^2 statistics given as shown in Equations 10 and 11, respectively (SAS, 2004; White and Bennetts, 1996; Agresti and Finlay, 1997):

$$D = 2\sum f_0 \log\left(\frac{f_0}{f_e}\right) \tag{10}$$

$$\chi^2 = \sum \frac{\left(f_0 - f_e\right)^2}{f_e} \tag{11}$$

Where:

f_o = observed frequency in a cell
f_e = expected frequency in a cell

The larger deviance values indicate a poor model fit to the data (Agresti and Finlay, 1997). If the model fits the data, both the deviance and the Pearson chi-square statistic divided by the degrees of freedom should be approximately equal to one (SAS, 2004). For a Poison model, the

D/DF and χ^2/DF values greater than one indicate that the variance is larger than the mean (overdispersion). Likewise, values smaller than one indicate that the variance is smaller than the mean (underdispersion).

3. Study results

SAS (version 9.3) software was used for the development of statistical models. The GENMOD procedure with the negative binomial was chosen to fit the generalized linear model. First, the models were run including all variables shown in Table 2. The variables which were found not to be statistically significant at $\alpha = 0.05$ were removed from the analysis, and then the models were re-run using only the significant variables including their interaction terms. The negative binomial generalized linear estimation results and their corresponding p-value statistics for merging and diverging crash models are shown in Tables 4 and 5, respectively.

Table 4
Negative binomial generalized linear estimation results for merging model

Variable	Estimated Coefficient	Std. Error	Wald 95% Confidence Limits		Wald χ^2	Pr > χ^2
			Lower	Upper		
Intercept	-5.8977	0.6425	-7.1569	-4.6385	84.27	<0.0001
MG	2.0644	0.1855	1.7008	2.4280	123.85	<0.0001
RC	0.6119	0.1409	0.3358	0.8881	18.87	<0.0001
LTC	0.7804	0.1451	0.4959	1.0649	28.91	<0.0001
WZ	1.3703	0.1794	1.0187	1.7219	58.34	<0.0001
AGE 1	-1.1679	0.1625	-1.4864	-0.8494	51.65	<0.0001
AGE 2	-2.0804	0.2253	-2.5220	-1.6389	85.27	<0.0001
Dispersion	5.4675	0.0561	3.4153	13.6986		

Table 5
Negative binomial generalized linear estimation results for diverging model

Variable	Estimated Coefficient	Std. Error	Wald 95% Confidence Limits		Wald χ^2	Pr > χ^2
			Lower	Upper		
Intercept	-3.6663	0.5575	-4.7590	-2.5736	43.25	<0.0001
DV	0.8143	0.1476	0.5249	1.1036	30.42	<0.0001
RC	0.8579	0.1457	0.5724	1.1434	34.69	<0.0001
LTC	0.9905	0.1521	0.6924	1.2886	42.42	<0.0001
WZ	1.0022	0.1751	0.6590	1.3455	32.76	<0.0001
AGE 1	-1.1329	0.1639	-1.4542	-0.8116	47.76	<0.0001
AGE 2	-1.6840	0.2181	-2.1114	-1.2565	59.62	<0.0001
Dispersion	3.701	0.0651	2.5149	7.008		

The p-value statistics show that all the variables included in the above tables are highly significant. Traffic volume, weather condition, presence of bridge, and the interactions between all the variables were found not significant. The results of model goodness of fit assessment for both merging and diverging crash models are depicted in Table 6. The model goodness of fit measures the fit between the observed data and the values predicted by the model. Table 6 results show that the negative binomial regression model fits well the study crash data for both models. The ratios of deviance and Pearson chi-square to degree of freedom (D/DF and χ^2/DF) for both models are close to one, which indicate good fit to the data.

Table 6

Criteria for assessing model goodness of fit results

Assessment Criterion	Merging Crash Model	Diverging Crash Model
Deviance (D)	80.9617	96.5861
Pearson chi-square(χ^2)	87.5148	95.1597
Log likelihood	1276.9541	1348.8633
Degrees of Freedom (DF)	82	95
D/DF	0.9873	1.0167
χ^2/DF	1.0673	1.0017

3.1 Elasticity

To represent the impact of independent variables on crash frequencies, elasticities were calculated for all variables. Equation 12 shows the formula for computing the elasticity for a continuous variable (Chang, 2005):

$$E_{x_{ij}}^{\lambda_i} = \frac{\partial \mu_i}{\partial x_{ij}} \cdot \frac{x_{ij}}{\mu_i} \tag{12}$$

Where

E = the elasticity due to variable *j* for section *i*

x_{ij} = the value of variable *j* for section *i*

μ_i = the mean of traffic crash frequency on section *i*

Then Equation 13 is developed as a result of combining Equations 12 and 2:

$$E_{x_{ij}}^{\lambda_i} = \beta_j x_{ij} \tag{13}$$

Where

β_j = the estimated coefficient for variable *j*

However, the elasticity defined above is applied to continuous variables only. For categorical variables, pseudo-elasticity can be defined and computed to obtain an approximate elasticity. Equation 14 shows how to compute the pseudo-elasticity for categorical variables:

$$E_{x_{ij}}^{\lambda_i} = \frac{\exp(\beta_j) - 1}{\exp(\beta_j)} \tag{14}$$

Table 7 shows the elasticity estimates for variables in both models. A variable to be considered elastic should have an absolute value larger than one. Based on the results in Table 7, merging left, diverging left, road condition, light condition, and work zone are the only elastic variables in both models. Elasticity values of the variables which are common in both models are relatively close.

Table 7
Elasticity estimates of variables in both models

	Elasticity Estimate	
Variable	Merging Model	Diverging Model
MG	3.3330	-
DV	-	1.5444
RC	1.3792	1.5832
LTC	1.5151	1.7088
WZ	2.1430	1.7205
AGE 1	0.5899	0.5984
AGE 2	0.4206	0.4836

3.2 Discussion of results

Two separate models were developed to establish a relationship between a number of variables and crash frequency using the negative binomial distribution. The purpose of developing the two models was to evaluate the effects of merging and diverging areas separately as the nature of crashes at these locations are always considered to be different.

The estimate for the variable accounting for the effect of the presence of merging areas on the left shows a positive coefficient of 2.0644 in Table 4, which is significantly greater than its corresponding value for diverging areas on the left in Table 5, which is 0.8143. This means that crashes are about 7.88 times more likely to occur on merging junctions located on the left side of the freeway lanes compared to those located on the right side. For diverging junctions, crashes are about 2.26 times more likely to occur near diverging areas located on the left side compared to those located on the right side of the freeway. The high speed differential between a vehicle trying to merge and vehicles traveling at high speed and occupying the left most lanes on the freeway may contribute to a larger number of accidents than would have been when compared with the right side merging locations.

The estimated coefficient for the variable representing adverse roadway conditions has a positive value in both models. This suggests that adverse roadway conditions such as wet pavement, snow, and ice are expected to cause about 1.84 and 2.36 times more crashes in the models developed for merging and diverging crash models, respectively. Similarly, adverse light conditions such as darkness and glare are found to result into about 2.18 and 2.69 times more crashes compared to normal daylight conditions at merging and diverging areas, respectively. The number of crashes in construction work zone areas was also found to be about 3.94 and 2.72 times higher than in segments with no construction activities in the vicinity of merging and diverging areas, respectively.

Age was used as a classification variable to study the effect of young drivers (less than 21 years of age) and senior drivers (65 years of age and above) compared to middle-age drivers (21-

64 years of age). The results of the analysis show that the expected number of crashes to be lesser by a factor of 0.12 for senior drivers and 0.31 for young drivers when compared with mid-age drivers in the merging model. Similarly, the expected number of crashes shows a decrease by a factor of 0.19 for senior drivers and 0.32 for young drivers when compared with mid-age drivers in the diverging model. This might sound counterintuitive as one expects an increase; however, knowledge on drivers' composition of the freeway user population can justify this result. Drivers of the age group 21-64 are the most active population of the society, highly involved in daily commute and long-distance driving when compared to the other two age groups considered in this study. In addition, young and senior drivers naturally tend to avoid high speed and high volume highways due to inexperience and deteriorating driving confidence, respectively.

4. Conclusions

This paper presented two models developed to estimate the expected number of traffic crashes on a typical urban freeway setting with unusual left side junctions. One of the models estimated the number of expected crashes for merging areas and the other one was for diverging areas. The negative binomial generalized linear model was used to develop the models. Among all the factors considered in this study, the presence of left-side junctions (both merging and diverging locations), driver's age, presence of a construction work zone, roadway pavement condition, and light condition were the only variables found significant in predicting the number of expected crashes. Although the number of left-side merging and diverging locations are very few compared to those located on the right side of the freeway in the study area, the expected number of crashes per left-side merging location is nearly 8 times higher than that of right-side location. In addition, the number of crashes occurring on a diverging area located on the left side of the freeway lanes is expected to be more than double of what's expected to occur on a similar area located on the right side. Moreover, adverse roadway and light conditions have been found to have significant effects on predicting the number of crashes for both merging and diverging area. The results of this model building effort can be used by local transportation agencies to gauge the performance of the transportation facility. In addition, the results may also be helpful in edifying transportation professionals on the safety benefits of the location of freeway junctions with respect to the mainline lanes. It is recommended that further studies of this nature be performed using data from a larger set of urban freeways by including a larger number and more diverse category of variables in order to build more comprehensive models.

References

Agresti, A., Finlay, B., 1997. Statistical methods for the social sciences, 3rd Edition, Prentice Hall, Upper Saddle River, NJ, USA.

Bared, J., Giering, L.G., Warren, L.D., 1999. Safety of evaluation of acceleration and deceleration lane lengths. ITE Journal 69, 50–54.

Bauer, K.M., Harwood, D.W., 1998. Statistical Models of accidents on interchange ramps and speed-change lanes, FHWA-RD-97-106.

Chang, L., 2005. Analysis of freeway accident frequencies: negative binomial regression versus artificial neural network. Safety Science 43(8), 541-557.

Chen, H., Liu, P., Lu, J.J., Behzadi, B., 2009. Evaluating the safety impacts of the number and arrangement of lanes on freeway exit ramps. Journal of Accident Analysis and Prevention 41(3), 543–551.

Chen, H., Lu, J.J., 2009. Evaluating the impacts of ramp configurations and influential factors on freeway exit ramps. Proceedings of the 9th International Conference of Chinese Transportation Professionals, Harbin, China.

Chen, H., Zhou, H., Zhao, J., Hsu, P., 2011. Safety performance evaluation of left-side off-ramps at freeway diverge areas. Accident Analysis and Prevention 43(3), 605–612.

Hauer, E., 2001. Overdispersion in modeling accidents on road sections and in empirical Bayes estimation. Accident Analysis and Prevention 33(6), 799–808.

Hauer, E., 2002. Observational before-after studies in road safety, 2nd Edition, Elsevier Science Ltd., Oxford, U.K.

Lee, C., Abdel-Aty, M., 2009. Analysis of crashes on freeway ramps by location of crash and presence of advisory speed signs. Journal of Transportation Safety and Security 1(2), 121-134.

Liu, P., Chen, H., Lu, J.J., Ciao, B., 2010. How lane arrangements on freeway mainlines and ramps affect safety of freeways with closely spaced entrance and exit ramps. Journal of Transportation Engineering 136(7), 614-622.

Lord, D., Washington, S.P., Ivan, J.N., 2005. Poisson, Poisson-gamma, and zero-inflated regression models of motor vehicle crashes: balancing statistical fit and theory. Accident Analysis and Prevention 37(1), 35–46.

McCartt, A.T., Northrup, V.S., Retting, R.A., 2004. Types and characteristics of ramp related motor vehicle crashes on urban interstate roadways in northern Virginia. Journal of Safety Research 35(1), 107–114.

Mergia, W.Y., Eustace, D., Chimba, D., Qumsiyeh, M., 2013. Exploring factors contributing to injury severity at freeway merging and diverging locations in Ohio. Accident Analysis and Prevention 55, 202-210.

Milton, J., Mannering, F., 1998. The relationship among highway geometrics, traffic related elements and motor-vehicle accident frequencies. Transportation 25(4), 395-413.

Moon, J. and Hummer, E.J. (2009). Development of safety prediction models for influence areas of ramps in freeways, Journal of Transportation Safety and Security 1(1), 1-17.

Pan, F.L., Chen, H., Lu, J.J., Cao, B., 2010. Safety impacts of closed-space interchanges and influences of auxiliary lanes. Journal of Transportation Engineering 136, 614–622.

Pedan, A., 2001. Analysis of count data using the SAS system, Paper 247-26. Proceedings of the 26th Annual SAS Users Group International Conference, Long Beach, CA, USA.

Poch, M., Mannering, F.L., 1996. Negative binomial analysis of intersection-accident frequency. Journal of Transportation Engineering 122(2), 105–113.

SAS Institute Inc., 2004. STAT® 9.1 User's guide. Cary, NC, USA.

Shankar, V., Mannering, F., Barfield, W., 1995. Effect of roadway geometrics and environmental factors on rural freeway accident frequencies. Accident Analysis and Prevention 27(3), 371-389.

Simonoff, J., 2003. Analyzing categorical data. Springer-Verlag, New York, NY, USA.

Sloboda, B.W., 2009. Transportation Statistics, Ross Publishing, Inc.

White, G.C., Bennetts, R.E., 1996. Analysis of frequency count data using the negative binomial distribution. Ecology 77, 2549-2557.

Zhao, J., Zhou, H. (2011). Safety of left exit on freeway: A case study in Florida, USA, Advances in Transportation Studies an International Journal 25, 75-90.

Zhou, H., Chen, H., Zhao, J. and Hsu, P. (2010). Operational and safety performance of left-side off-ramps at freeway diverge areas. TRB 2010 Annual Meeting CD-ROM, Washington, DC, USA.