Injury Severity Analysis of Crashes in Right-Turn Lanes at Signalized Intersections

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Abstract

This study investigated the level of injury severity in crashes in right-turn lanes at signalized intersections. It used a dataset of 1900 injuries occurring at 275 signalized intersections in the Las Vegas area in the 2003 to 2005 period. An advanced random parameter binary logit model was used to determine the factors that significantly influence injury severity with PDO and severe injury in right-turn lanes. A comparison of this model with the traditional fixed parameter model was made to account for the unobserved heterogeneity. It was comparable to the two-level binary logistic model, which accounts for cross-group heterogeneity. The analysis showed that the following factors lead to a significantly higher likelihood of severe injury: rear-end crashes, the involvement of a vehicle going through the intersection, stopped and parked vehicles on main and minor streets, length of corner clearance, number of through lanes on minor streets, and intersection angle.

Keywords: Injury Severity; Right-turn Lane; Random Parameter Binary Logit Model; Two-level Binary Logistic Model

List of Notations

Acronyms

NDOT	Nevada Department of Transportation
AADT	Annual Average Daily Traffic
PDO	Property Damage Only
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion

Parameters

$\mathrm{Y_i}$	Dependent variable
X_{ik}	Matrix of independent variable
β_0	Intercept
β_k	Regression coefficients
β_{ik}	Matrix of coefficient
φ_{ik}	Standard normal distribution function
σ_k^2	Variance
L	Likelihood of the data
m	Number of parameters
n	Number of observations
ρ^2	McFadden's adjusted pseudo value
$LL(\mathbf{0})$	Log likelihood at zero
$LL(\boldsymbol{\beta})$	Log likelihood at convergence

Introduction

Intersections are the main nodes in urban roadway networks, where traffic streams merge, turn, interact, and diverge. The interactions of traffic streams at intersections produce various conflict points, which increase the risk of traffic crashes.

Right-turn lanes in North America are designed to provide space for the deceleration and storage of turning vehicles and to separate turning vehicles from through vehicles. Their purpose is to ameliorate safety and/or vehicle operations at intersections. However, crashes may even increase with the introduction of right-turn lanes due to collisions between right-turning vehicles and vehicles going straight through the intersection in the same direction or due to conflicts between right-turning vehicles and vehicles moving straight through the intersection in the same direction. The latter conflict can lead to a grid-lock of the whole intersection. Therefore, it is necessary to investigate the conflicts and to identify the factors that influence injury severity in right-turn lanes crashes.

Literature Review

A number of approaches and perspectives have been used to model crash injury severity. Econometric modeling approaches have focused on overall safety and economic implications. Savolainen et al. (2011) summarized the common models used in the analysis of crash injury severity including artificial neural networks, Bayesian hierarchical binomial logit, Bayesian-ordered logistic, bivariate binary/ordered logistic, classification and regression tree, generalized ordered logit, Markov-switching multinomial logit, mixed/generalized ordered logit, multivariate logit/logistic, nested logit, ordered logit/logistic models, partial proportional odds model, etc. The various modeling approaches are commonly categorized into two types for the evaluation of injury severity: ordered response types and unordered response types (Abay, 2013).

As injury severity data are inherently ordered, the ordinal nature of response outcomes needs to be accounted for in the modeling framework. Therefore, most studies of injury severity have used ordered response models, particularly ordered logit or ordered probit models. Examples of previous studies that have used ordered response models to analyze injury severity are Abdel-Aty (2003), Eluru and Bhat (2007), Sze and Wong (2007), Wang and Abde-Aty (2008), Eluru et al. (2008), Clifton et al. (2009), Kwigizile et al. (2011), Mohamed et al. (2013), Abay (2013), and Saidharan and Menendez (2014). .

However, as stated by Savolainen et al. (2011), Washington et al. (2011), Abay (2013), and Saidharan and Menendez (2014), one of the key assumptions of ordered response models is that the effects of the independent variables are fixed throughout the observations; this may easily lead to biased empirical inferences. Some recent studies have improved the ordered response models by introducing the generalized ordered logit model (Eluru et al., 2008; Saidharan and Menendez, 2014), generalized probit model (Clifton et al., 2009), and a latent class with an ordered probit model (Mohamed et al., 2013). These expanded approaches have taken into account the unobserved heterogeneity of different levels of injury severity. Unordered response models (multinomial, nested, and mixed logit/probit) have also been widely used to evaluate injury severity (Carson and Mannering, 2001; Ulfarsson and Mannering, 2004; Kim et al., 2008, 2010; Tay et al., 2011; Abay, 2013; Aziz et al., 2013; Saidharan and Menendez, 2014). Although they do not capture the ordinal features of the injury severity levels, these models allow all of the independent variables to show different levels of the dependent variables distinctively, which is necessary to explain the more flexible variable effects on the dependent variables. However, as these models cannot account for the ordered nature inherent in injury severity, they may suffer from the assumption that unobserved heterogeneity is independent, an assumption that is inconsistent with an ordered framework (Train, 2009).

Various approaches have been adopted to evaluate right-turn lane safety. To examine crashes in right-turn lanes, Villaluz (2006) used a simple bivariate regression and multiple regression analysis to analyze the factors related to right-turn lanes at High Crash Locations (HCLs) in the Las Vegas Valley. Chen et al. (2014) used simulations to verify that dual right-turn lanes can significantly decrease weaving conflicts compared to a single right-turn lane designs at frontage road intersections. Sayed et al. (2013) made practical improvements to right-turn safety at intersections in Edmonton, Alberta, Canada, which alleviated the high rate of rear-end and merging crashes. Using video data collected with an automated traffic safety tool, they found that the changes significantly decreased rear-end, merging, and total conflicts. Dabbour and Easa (2014) used a two-way stop-controlled pattern perceptual framework to aid unprotected right-turning drivers at rural intersections.

A few models have been developed to examine injury severity in crashes at intersections. Bauer and Harwood (2000) found that right-turn channelization decreased the number of multiple-vehicle fatal and injury crashes. Al-Ghamdi (2002) used the binary logit model to investigate the relationship between crash characteristics and their causes and the severity of injuries in crashes involving right-turn vehicles. Recent studies by Autey et al. (2012) and Sacchi et al. (2013) conducted full Bayes safety evaluations for channelized right-turn lanes that had angles of approximately 70 degree in Penticton, British Columbia. Full Bayes univariate and multivariate linear intervention models were used and the results showed that the implementation of the right-turn lane produced an obvious decrease in collision severity. The latest study by Ale et al. (2014) investigated crashes over a five-year period in Minnesota’s two-lane trunk highways. Using a logistic regression model, they examined the effects that right-turn lanes and right-turn movements had on safety at uncontrolled major road approaches to intersections/driveways. The conclusions were that the crashes caused by right-turning vehicles were less severe (mostly property damage), and that injury severity levels in the crashes caused by right-turn-vehicles were significantly associated with posted speed limits, right-turn treatments, and road surface conditions.

As summarized in Table 1, previous studies have not deeply explored right-turn lane safety. Research has focused on the use of cross-sectional modeling to identify the factors that influence right-turn crashes; few studies have used panel data modeling. Furthermore, as stated by Hauer (2010), cross-sectional studies have produced controversial cause-effect conclusions. This study used a panel data binary logistic regression model to determine the factors that significantly influence right-turn lane crashes, and investigated heterogeneity among the signalized intersections.

Data Description

This study used a dataset of injuries occurring in the 2003 to 2005 period at 275 signalized intersections located at 27 major and minor arterials in the Las Vegas Metropolitan area (Clark County, City of Las Vegas, City of North Las Vegas, and City of Henderson) to identify the significant factors in crashes in right-turn lanes. Data were collected from 275 signalized intersections with right-turn lanes.

A geographic information system (GIS) and Google Earth were used to examine the selected signalized intersections.. Although there are 400 intersections listed in Table 2, some intersections had more than one observation, as each midblock included two intersections, so the intersection was counted twice. After eliminating the duplicates, the final sample included 275 signalized intersections (including three-legged and four-legged signalized intersections). Table 2 gives the number of signalized intersections on each arterial road, and Figure 1 shows the exact locations of the selected signalized intersections.

The original crash dataset was obtained from the NDOT. The crashes were counted for each intersection using a buffer area centered at the cross-point of the intersection. Any crashes involving right-turning vehicles that occurred within the buffer area were considered to have happened within the intersections. The radius of the buffer area was set as 60.96 m (200 ft). Figure 2 shows the buffer area crashes for the intersection at Flamingo Road and Swenson Street. In 2004, there were 114 crashes at this intersection, including 4 right-turn crashes.

The other variables of interest, including the number of lanes at each approach (including left-turn, through, and right-turn only lane), the average speeds, and average corner clearances were collected for each intersection using a GIS map combined with Google Earth (More details can be obtained from Xu et al. [2014]). The annual average daily traffic (AADT) of the approach was used as the criteria to determine which road was the primary road at each intersection.

In this study, 1900 injuries resulting from right-turn movements were extracted from the dataset from more than 40,000 data bars, in which 1444 injuries (76%) and 456 injuries (24%) are attributed to PDO and severe injury respectively, and 23 variables were examined as potentially significant factors in the severity of right-turn-related crashes. Xu et al. (2014) provided a detailed description of the variables mentioned above. Crash data were classified into types using the categories shown in Table 3. The category "angle crashes" includes crashes related to both right-angle turns from non-opposing angular directions and angular collisions from opposite directions; rear-end crashes are collisions between vehicles moving in the same direction, i.e., the front end of the following vehicle strikes the rear end of the leading vehicle; sideswipe crashes can be collisions between vehicles moving in the same directions or in opposite directions. Table 4 presents the descriptive statistics for the selected variables.

Methodology

Fixed parameter binary logit model

There are two main classification systems for injury severity. The first is the "KABCO" scale, with "K" through "O" representing five levels of severity: fatal injury, incapacitating injury, non-incapacitating evident injury, possible injury, and non-injury. The second scale uses three categories: fatality, injury, and property damage only (PDO). The NDOT dataset uses the second system. As there were no fatalities related to right-turn crashes in the dataset used in this study, all of the observations were either "injury" or "PDO." The dichotomous nature of the injury outcome facilitates the application of a binary logistic regression model. The response variable Y for the ith pedestrian crash only takes one of two values: $Y_i = 1$ in the case of severe injury, and $Y_i = 0$ in the case of PDO. The probability of $Y_i = 1$ is denoted by $\pi_i = \Pr(Y_i = 1)$, which follows a binomial distribution, hence

$$\text{logit}(\pi_i) = \log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \sum_{k=1}^{p} \beta_k X_{ik} \quad (1)$$

,

where X_{ik} is the kth explanatory variable for the ith right-turn crash, and β_0 and $\beta_k (k = 1, ..., p)$ are the intercept and regression coefficients, respectively.

Random parameter binary logit model

As demonstrated in Milton et al. (2008) and Washington et al. (2011), the random parameter logit model can be used to evaluate the crash severity levels of specific roadway segments within a certain time period, while also accounting for unobserved heterogeneity, even with limited data. In this study, the random parameter binary logit model was used to account for crash-specific variations in the effects of the explanatory variables on the propensity for injury in right-turn lane crashes. The model can be expressed as

$$\begin{aligned} &\operatorname{logit}(\pi_i) = \log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_{i0} + \sum_{k=1}^{P} \beta_{ik} X_{ik} \\ &\beta_{ik} = \beta_k + \varphi_{ik} \end{aligned} \quad , \tag{2}$$

where β_{ik} is the coefficient of the kth explanatory variable for the ith crash, and φ_{ik} is a randomly distributed term (e.g., a normally distributed term with mean 0 and variance σ_k^2). Practically, a random parameter β_{ik} is used whenever $\widehat{\sigma}_k$ is significantly greater than 0, otherwise the parameter β_k is fixed across the observations.

The estimation of the above random parameter binary logit model was undertaken using the simulated maximum likelihood approach with 200 Halton draws (Anastasopoulos and Mannering, 2011)..

As the coefficients of a random parameter binary logit model cannot directly explain variation in the variables, the influence of the kth attribute on injury severity levels was determined using the odds ratio:

$$\text{odd ratio} = \exp(\beta_k) \quad . \tag{3}$$

A value significantly larger than 1 implied that the variable included may induce a higher risk of injury.

Measures of goodness of fit

Generally, more predictors improve the likelihood value of the proposed model; however, too many variables may lead to over-fitting (Saidharan and Menendez, 2014). To prevent this problem, AIC and BIC are introduced by including a penalty term for the number of predictors along with the likelihood values of the model.. The lower the AIC and BIC values, the better the statistical fit of the model. The AIC and BIC can be estimated by

$$\text{AIC} = -2\log(L) + 2m \text{ and} \tag{4}$$

$$\text{BIC} = -2\log(L) + m\log n, \tag{5}$$

where L is the likelihood of the data given the proposed model, m is the number of parameters, and n is the number of observations.

The overall fit of the models can also be determined by calculating McFadden's adjusted pseudo ρ^2 (Abay 2013), which compares the log-likelihood value at convergence and the log-likelihood value at zero. More explicitly, it can be calculated as

$$\rho^2 = 1 - \frac{LL(\boldsymbol{\beta}) - m}{LL(\mathbf{0})} \quad , \tag{6}$$

where $LL(\boldsymbol{\beta})$ and $LL(\mathbf{0})$ are the log-likelihood values at convergence and at zero, respectively.

Results and Discussion

Each of the explanatory variables given in Tables 3 and 4 were checked for statistical correlations. Both the fixed parameter binary logit model and random parameter binary logit model were run using *STATA 12.0* software. The correlation test between selected variables identified four variables, number of lanes on main street and minor street, land use type, , and average speed on minor street, which were highly correlated with other variables, so they were removed to avoid the interaction between them. Table 5 gives the final model results for the fixed parameter binary logit model and random parameter binary logit model at the 95% confidence interval.

The results of the likelihood-ratio test, shown in Table 5, showed that the random parameter model provided a slightly superior fit. The McFadden's adjusted pseudo ρ^2, AIC, and BIC values revealed that the random parameter partner had better goodness of fit.

Given the existence of heterogeneity in the dataset, cross-group heterogeneities needed to be addressed to avoid underestimating the standard errors in the regression coefficients (Huang and Abdel-Aty, 2010). Following the multilevel data structure presented by Huang and Abdel-Aty (2010), a two-level binary logistic model was established to address the potential cross-intersection heterogeneity, and the results were compared with the models above. Table 6 presents the results.

Table 6 shows that the two-level binary logistic model is similar to the fixed parameter binary logit model, but is a bit different from the random parameter binary logit model. The fixed parameter binary logit model and the two-level binary logistic model had the same number of parameters; the random parameter binary logit model had more than either of them. McFadden's adjusted pseudo ρ^2 for the two-level binary logistic model was larger than the pseudo ρ^2 value of the two other models, but the AIC value (AIC=602.37) for the two-level binary logistic model was smaller, and the BIC (BIC=658.78) value was higher than for the two other models. The AIC and BIC values for the random parameter model were smaller than those for the fixed parameter model. These results indicated that the two-level binary logistic model was comparable to the two other models.

The results for the random parameter binary logit model, given in Table 5, show that the following variables were statistically significant: crash type (CRTYP), movement of vehicle on main streets (MAINRT), movement of vehicle on minor streets (MINORRT), number of through lanes on minor streets (TRMINOR), length of corner clearance (NOCC), and intersection angle (ANGLE).

The results for the random parameter binary logit model, given in Table 5, show that the following factors were significantly related to a higher probability of severe injury: rear-end crash type (odds ratio=1.370), going straight (6.143), and stopped and parked vehicles on main streets (5.100), going straight (3.360), and stopped and parked vehicles on minor streets (3.720), number of through lanes on minor streets (1.990), length of corner clearances (2.450), and intersection angle (2.960).

The results for the rear-end crashes were normally distributed with a mean of 0.311 and a standard error 0.126. The odds ratio was larger than 1, indicating that rear-end crashes may be associated with a higher injury risk. Rear-end crashes were the most frequent type of crashes in the right-turn lanes, and were mainly due to the drivers' inattention, inappropriate braking, or speeding while turning right at a signalized intersection. Similar findings were reported in a previous study by Ale et al. (2014).

The movement of vehicles on main streets and minor streets was significantly associated with higher injury risk; incidents in which the vehicle was going straight or stopped/parked were more severe when the vehicle swerved abnormally rather than turning right. Collisions between right-turning vehicles and straight-through vehicles or between right-turning vehicles and opposing straight-through vehicles were equally likely to lead to a severe injury, and the worst cases could cause a grid-lock of the whole intersection. If a driver behaves in a disorderly or aggressive manner, other drivers may not have sufficient time to react, even if the vehicles are already stopped/parked. In these scenarios, crashes are more likely to be severe.

Unexpectedly, another significant factor related to injury severity was the number of through lanes on minor streets. The fewer the number of through lanes on the minor streets, the greater the chance of conflicts and the more dangerous the vehicles' movements. In these environments, drivers need to be more careful when turning right.

Another significant variable was the length of the corner clearance, which is a factor that can be controlled through access management. A longer corner clearance may help drivers of through traffic perceive and respond more adequately to other drivers and to turn into adjacent accesses, thus decreasing the number of crashes. A shorter corner clearance may not allow drivers enough time to react, thus causing more conflicts between turning and through traffic. Similar findings were reported in a previous study by Xu et al. (2014).

Among all of the geometric design factors, the intersection angle had the strongest association with injury risk, implying that drivers' visual range may be affected by the angle. Inadequate angles result in less response time. Various right-turn treatments have been presented to address this issue; Smart Channels developed by Autey et al. (2012) and Sacchi et al. (2013) provided empirical evidence for the benefits of a channelized right-turn of approximately 70 degrees.

Conclusions

This study evaluated the effects of various factors on injury severity in right-turn lane crashes. The unobserved missing factors were investigated using random parameter binary logit models and a crash dataset from the Las Vegas area. Although right-turn crashes are usually not severe, in this database more than three quarters were PDOs; therefore, it is important to identify the factors that influence crash severity as the number of car owners is increasing sharply. Once the significant factors are confirmed, measures can be taken to reduce crash severity.

The analysis revealed some key findings. First, rear-end crashes, crashes involving vehicles going straight or stopped/parked on main and minor streets, the number of through lanes on minor streets, the length of corner clearance, and the intersection angle significantly affected the severity of right-turn lane crashes.

Second, both the fixed parameter binary logit model and random parameter binary logit model were estimated and then compared with the two-level binary logit model. The random parameter binary logit model provided a more sensitive result than the fixed parameter model and was comparable to the two-level binary logit model in terms of goodness of fit. One advantage of the two-level binary logit model is its ability to account for the cross-group heterogeneities among different signalized intersections. An approach that integrates these two models should be developed in future studies.

Finally, the findings of the modeling analysis suggest that safety planners need to improve the markings or signs at intersections where rear-end crashes in right-turn lanes are common. Safety policymakers also need to consider providing education programs for drivers with risky behavior to reduce the potential risk of right-turn crashes at signalized intersections. Furthermore, longer corner clearances need to be designed around the signalized intersections to reduce the severity of injuries in crashes. Designers also need to control the number of through lanes on minor streets and choose appropriate intersection angles when designing right-turn lanes. All of these countermeasures could increase safety and mobility, and alleviate the risks of right-turn lane crashes at signalized intersections.

Future studies should examine the combined effects of these factors. It is beneficial to have engineers make evaluations before an intersection is built, to help detect potential risks. With the increasing number of automobiles, traffic crashes have become a more urgent social problem, and more studies on injury severity are necessary. Furthermore, more detailed crash information would help researchers to identify more factors that influence traffic crashes.

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FIGURE CAPTIONS LIST

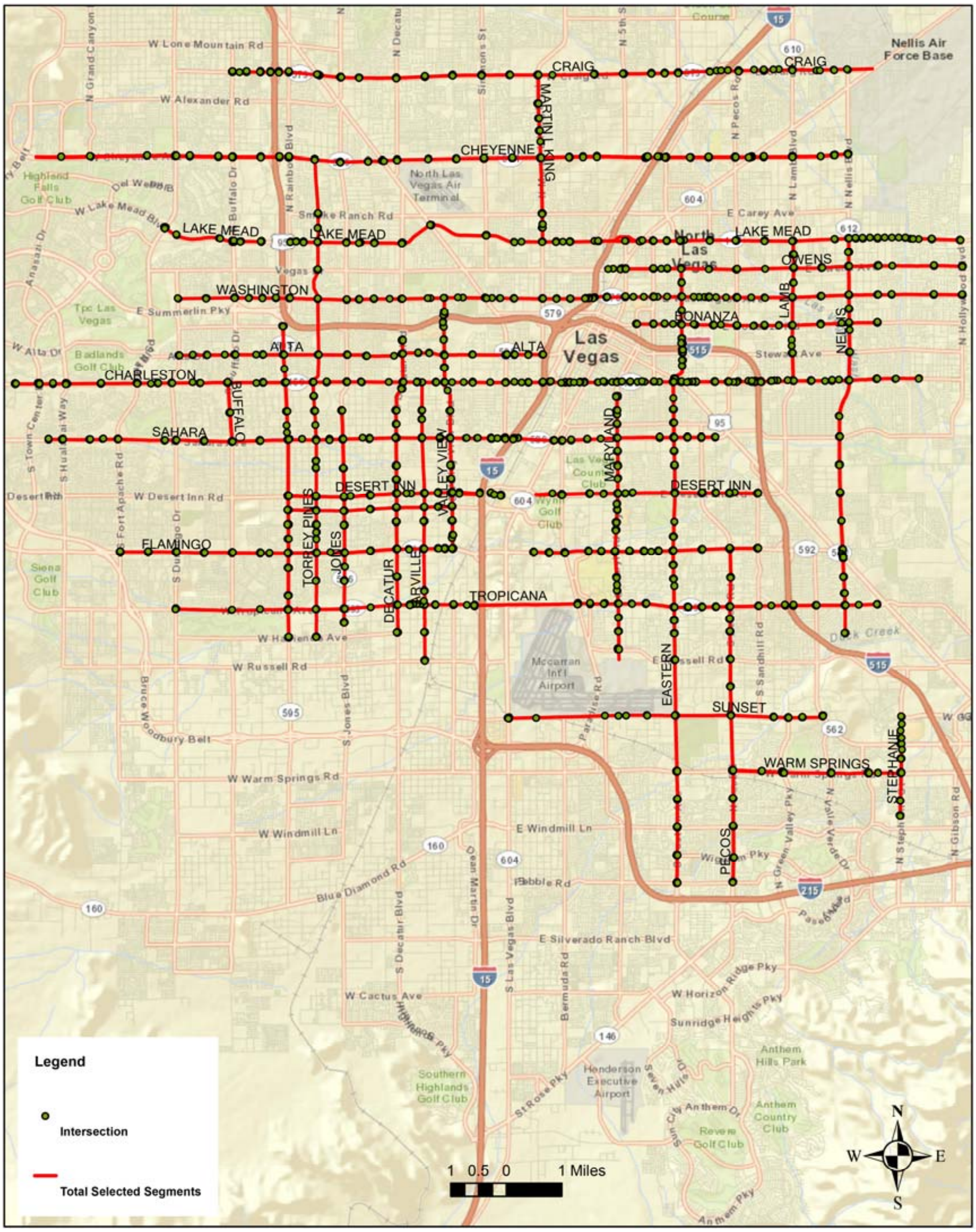

Figure.1. Selected intersections in Las Vegas area

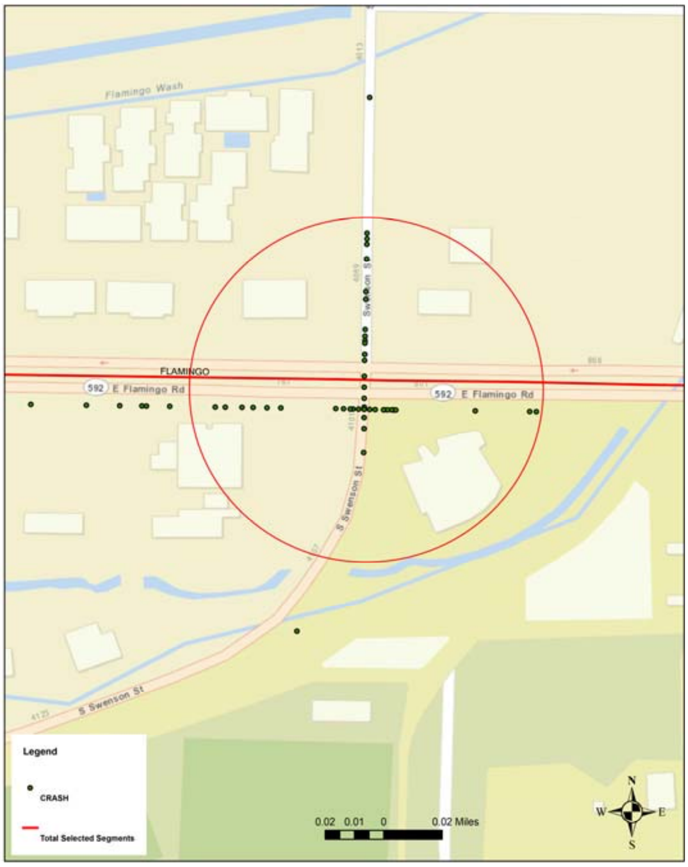

Figure.2. Intersection at Flamingo Rd. and Swenson St.

TABLE CAPTION LIST

Table1. Summary of Previous Studies

Perspective		Authors	Features
General injury severity	Summary	Savolainent et al. (2011)	Summarized the models and methods used to assess injury severity.
	Ordered response framework	Abdel-Aty (2003), Eluru and Bhat (2007), Sze and Wong (2007), Wang and Abde-Aty (2008), Eluru et al. (2008), Clifton et al. (2009), Kwigizile et al. (2011), Mohamed et al. (2013), Abay (2013), Saidharan and Menendez (2014)	When the different severity levels are inherently ordered, it is easy to capture the relations between different severity levels.
	Improved ordered response framework	Eluru et al. (2008), Saidharan and Menendez (2014), Clifton et al. (2009), Mohamed et al. (2013)	They take into account the unobserved heterogeneity across different injury severity levels.
	Unordered response framework	Carson and Mannering (2001), Ulfarsson and Mannering (2004), Kim et al. (2008, 2010), Tay et al. (2011), Abay (2013), Aziz et al. (2013), Saidharan and Menendez (2014)	These models allow all of the independent variables to show different levels of the dependent variables distinctively.
Unsignalized intersection	Crashes	Villaluz (2006)	Bivariate regression analysis and multiple regression analysis were used to analyze the right-turn related crashes.
	Simulation	Chen et al. (2014)	They evaluated right-turn lane safety using microscopic simulation.
	Practice	Sayed et al. (2013), Dabbour and Easa (2014)	Video data were used to measure traffic conflicts with an automated traffic safety tool.
Signalized intersection	Channelization	Bauer and Harwood (2000)	Right-turn channelization led to a decrease in multiple-vehicle fatalities and injuries.
	Binary logit model	Al-Ghamdi (2002)	Right-turn vehicles were found to influence injury levels.
	Linear intervention models	Autey et al. (2012), Sacchi et al. (2013)	The implementation of the right-turn treatment has considerably decreased collision severity.
	Logistic regression model	Ale et al. (2014)	The severity of injuries was significantly associated with posted speed limits, right-turn treatments, and road surface conditions.

Table2. Summary of Selected intersections

No.	Arterial	Section		Direction	Intersection number
		Begin	End		
1	Ann Road	N. Rainbow Boulevard	N. Simmons Street	WE	6
2	Bonanza	N. Maryland Parkway	N. Hollywood Boulevard	WE	11
3	Buffalo Drive	W. Charleston Boulevard	W. Sahara Avenue	NS	6
4	Charleston Boulevard	Pavilion Center Drive	Tree Line Drive	WE	32
5	Cheyenne Avenue	N. Hualapai Way	N. Rancho Drive	WE	13
6	Craig Road	N. Buffalo Drive	Las Vegas Boulevard	WE	21
7	Decatur Boulevard	Meadow Lane	W. Hacienda Avenue	NS	16
8	Desert Inn Road	S. Rainbow Boulevard	S. Sandhill Road	WE	17
9	Eastern Avenue	E. Pebble Road	E. Owens Avenue	NS	22
10	Flamingo Road	S. Fort Apache Road	S. Sandhill Road	WE	27
11	Jones Boulevard	W. Oakey Boulevard	Foothill Boulevard	NS	11
12	Lake Mead Boulevard	N. Rainbow Boulevard	N. Hollywood Boulevard	WE	17
13	Lamb Boulevard	E. Lake Mead Boulevard	E. Charleston Boulevard	NS	7
14	Martin L King Boulevard	W. Craig Road	W. Lake Mead Boulevard	NS	6
15	Maryland Parkway	Franklin Avenue	E. Russell Road	NS	14
16	Nellis Boulevard	E. Lake Mead Boulevard	E. Hacienda Avenue	NS	17
17	Owens Avenue	Main Street	N. Hollywood Boulevard	WE	12
18	Pecos Road	E. Flamingo Road	Pebbles Road	NS	13
19	Rainbow Boulevard	Westcliff Drive	W. Hacienda Avenue	NS	13
20	Sahara Avenue	Blue Willow Lane	S. Mojave Road	WE	30
21	Spring Mountain Road	Rainbow Boulevard	Valley View Boulevard	WE	8
22	Stephanie Street	Galleria Drive	American Pacific Drive	NS	6
23	Sunset Road	S. Eastern Avenue	Mountain Vista Street	WE	8
24	Tropicana Avenue	S. Durango Drive	Andover Drive	WE	27
25	Valley View Boulevard	Meadows Lane	W. Flamingo Road	NS	13
26	Warm Spring Road	S. Eastern Avenue	N. Stephanie Streets	WE	5
27	Washington Avenue	N. Durango Drive	N. Hollywood Boulevard	WE	23

Table 3. Classification of Variables

Abbreviation	Variable description	Count	Proportion (%)
Cash type	Angle	1302	68.55
	Rear-end	447	23.53
	Sideswipe, overtaking	84	4.42
	Others	67	3.50
MAINRT	Turning right	1209	63.63
	Going straight	407	21.42
	Turning left	81	4.26
	Stopped/Parked	68	3.58
	Others	135	7.11
MINORRT	Turning right	893	47.00
	Going straight	534	28.11
	Turning left	78	4.11
	Stopped/Parked	195	10.26
	Others	200	10.52

Table 4. Summary of Descriptive Statistics

Abbreviation	Variable description	Mean	Std. Dev.	Min.	Max.
RTTNMAIN	Number of right-turn lanes on main streets	0.566	0.547	0	2
RTMINOR	Number of right-turn lanes on minor streets	0.434	0.530	0	2
LANDUSE	Land use types; 1 is for commercial, 0 is for residential	0.912	0.201	0	1
NOCC	Length of corner clearances	6.446	1.717	1	8
NOMAINLN	Number of lanes on main street	8.029	1.126	3	11
LFTNMAIN	Number of left-turn lanes on main street	1.689	0.615	0	2
TRMAIN	Number of through lanes on main street	5.774	0.900	0	8
NOMINORLN	Number of lanes on minor street	6.660	1.571	2	9
LFTNMINOR	Number of left-turn lanes on minor street	1.504	0.524	0	2
TRMINOR	Number of through lanes on minor street	4.720	1.373	0	6
EWAVGCC	Average corner clearance in eastbound-west bound, ft	171.667	103.481	0	636.00
NSAVGCC	Average corner clearance in northbound-south bound, ft	166.039	80.328	0	752.00
EWFL/1000	Total traffic flow in eastbound-westbound by 1000	85.970	39.840	2.02	175.7
NSFL/1000	Total traffic flow in northbound-southbound by 1000	69.486	34.111	1.82	147
MAINAVGSP	Average speed on main street, mph	43.091	4.158	25	45
MINORAVGSP	Average speed on minor street, mph	36.268	7.747	15	45
ANGLE	Intersection angle, degree	86.533	6.431	33.47	90.00
EWGRADE	Eastbound-westbound grade	0.051	0.650	-1.73	4.69
NSGRADE	Northbound-southbound grade	0.028	0.624	-2.36	1.99

Table 5 Estimation Results of the Two Final Models

		Fixed parameter			Random parameter		
Variables	Control	Coefficient	Std. Err.	Odds ratio	Coefficient	Std. Err.	Odds ratio
Crash type β 1							
Angle, β 1.1	Others	-0.369	0.229	0.691	-0.373	0.214	0.687
Rear-end, β 1.2		0.357	0.166	1.430*	0.311	0.126	1.370*
Sideswipe, overtaking, β 1.3		-0.467	0.129	0.627	-0.580	0.110	0.559
MAINRT β 2	Others						
Turning right, β 2.1		1.118	0.115	3.089	1.159	0.113	3.186
Going straight, β 2.2		1.814	0.249	6.140*	1.816	0.224	6.143*
Turning left, β 2.3		0.190	0.164	1.209	0.212	0.182	1.235
Stopped/Parked, β 2.4		1.668	0.193	4.800*	1.630	0.200	5.100*
MINORRT β 3	Others						
Turning right, β 3.1		0.924	0.180	2.280	0.954	0.134	2.594
Going straight, β 3.2		1.234	0.158	3.200*	1.212	0.154	3.360*
Turning left, β 3.3		0.027	0.186	1.091	0.021	0.194	1.022
Stopped/Parked, β 3.4		1.394	0.172	3.300*	1.314	0.136	3.720*
TRMINOR, β 5		-	-	-	-0.400	0.148	1.990*
NOCC, β 6		-	-	-	-0.134	0.150	2.450*
ANGLE, β 12		-	-	-	-0.017	0.005	2.960*
Constant		-3.203	0.185	0.410*	-3.206	0.183	0.405*
Goodness-of-fit							
Number of observations, n			1900			1900	
Number of parameters, m			11			14	
Log likelihood at zero, $LL(\mathbf{0})$			-312.100			-303.050	
Log likelihood at convergence, $LL(\boldsymbol{\beta})$			-303.400			-299.415	
McFadden's adjusted pseudo ρ^2			0.058			0.063	
AIC			614.80			610.83	
BIC			632.20			615.40	

Table 6. Results for the Two-Level Binary Logistic Model

Variables	Control	Coefficient	Std.Err.	Odds ratio
Crash type β 1				
Angle, β 1.1	Others	-0.374	0.207	0.688
Rear-end, β 1.2		0.311*	0.141	1.366*
Sideswipe, overtaking, β 1.3		-0.580	0.115	0.560
MAINRT β 2	Others			
Turning right, β 2.1		1.158	0.110	3.187
Going straight, β 2.2		1.815*	0.244	6.144*
Turning left, β 2.3		0.212	0.161	1.236
Stopped/Parked, β 2.4		1.630*	0.185	5.102*
MINORRT β 3	Others			
Turning right, β 3.1		0.953	0.174	2.595
Going straight, β 3.2		1.211*	0.104	3.358*
Turning left, β 3.3		0.021	0.179	1.022
Stopped/Parked, β 3.4		1.314*	0.167	3.720*
Constant		-3.205*	0.180	0.405*
Goodness-of-fit				
Number of observations, n			1900	
Number of parameters, m			11	
Log likelihood at zero, $LL(\mathbf{0})$			-296.690	
Log likelihood at convergence, $LL(\boldsymbol{\beta})$			-288.190	
McFadden's adjusted pseudo ρ^2			0.65	
AIC			602.37	
BIC			658.78	

Note: * indicates the variable is significant at the 5% level of significance.