Modern Applied Science; Vol. 12, No. 4; 2018
ISSN 1913-1844 E-ISSN 1913-1852
Published by Canadian Center of Science and Education

Negative Binomial Regression Model for Road Crash Severity Prediction

Hana Naghawi[1]

[1] Civil Engineering Department, School of Engineering, The University of Jordan, Amman, Jordan.

Correspondence: Hana Naghawi, Civil Engineering Department, School of Engineering, The University of Jordan, Amman 11942, Jordan. Tel: 962-6535-5000. E-mail: hana_naghawi@yahoo.com

Received: February 27, 2018 Accepted: March 6, 2018 Online Published: March 19, 2018

doi:10.5539/mas.v12n4p38 URL: https://doi.org/10.5539/mas.v12n4p38

Abstract

In this paper, the Negative Binominal Regression (NBR) technique was used to develop crash severity prediction model in Jordan. The primary crash data needed were obtained from Jordan Traffic Institute for the year 2014. The collected data included number and severity of crashes. The data were organized into eight crash contributing factors including: age, age and gender, drivers' faults, environmental factors, crash time, roadway defects and vehicle defects. First of all, descriptive analysis of the crash contributing factors was done to identify and quantify factors affecting crash severity, then the NBR technique using R-statistic software was used for the development of the crash prediction model that linked crash severities to the identified factors. The NBR model results indicated that severe crashes decreased significantly as the age of both male and female drivers increased. They significantly decreased as the environmental conditions improved. In addition, sever crashes were significantly higher during weekdays than weekends and in the morning than in the evening. The results also indicated that sever crashes significantly increased as drivers have faults while driving. In addition, mirror and brake deficits were found to be the only factors among all possible vehicle deficits factors that contributed significantly to severe crashes. Finally, it was found that the results of the NBR model are in agreement with the descriptive analysis of the crash contributing factors.

Keywords: safety, crash prediction model, negative binomial regression, crash analysis, statistical methods

1. Introduction

Motor vehicle travel is the primary mode of transportation in the world. It provides high degree of mobility. But the resulting road traffic crashes are considered the leading cause of death, with disproportionate number occurring in developing countries (WHO, 2014; Murray & Lopez, 1996). Jordan, one of the developing countries, suffers from this problem. Jordan traffic institute statistics reported that 144,521 traffic crashes occurred during the year 2016, as a result 750 people lost their lives, and 17,435 people have been injured. The death rate in the same year was 2.1 fatalities per day, 4.99 fatalities per 10,000 vehicles, 7.65 fatalities per 100,000 population. The injury rate, for the same year, was 47.8 injuries per day, 116 injury per 10,000 vehicles, and 177.9 injury per 100,000 population, with an estimated cost of crashes JD 323 million (JTI, 2016).

Table 1 shows number of crashes, fatalities, number of registered vehicles, population and crash cost for the period (2007-2016). It can be seen that during the ten year period, there has been an increase of almost 78.50 percent in vehicle ownership accompanied by 57.64 percent reduction in fatality rate per 10,000 vehicles, and 55.49 percent reduction in fatality rate per 10,000 persons. The latter may be attributed to the larger increase in the number of population over the study period (JTI, 2016). This may occurred as a result of the political situation of the neighboring countries of Jordan, which led to increase the number of arrivals to Jordan. Also, it can be seen that traffic crashes are very costly for a developing country with limited resources such as Jordan. The average cost of traffic crashes in Jordan for the ten year period was estimated to be about JD 277.25 million. This is equivalent to about 0.72 percent of the gross domestic product of Jordan which is about JD 54.44 billion (Global Finance, 2016).

Table 1. Number of Crashes, Vehicle Ownership, Fatalities, and Fatality Rates in Jordan

Year	Crash	Fatally	Registered Veh.	Population $1*10^6$	Fats/10,000 Veh.	Fats/10,000 Persons	Veh./10,000 Persons	Severity Rate	Cost (10^3JD)
2007	110630	992	841933	5723	11.78	1.73	1471.14	0.17	281
2008	101066	740	905592	5850	8.17	1.26	1548.02	0.14	245
2009	122793	676	994753	5980	6.80	1.13	1663.47	0.13	258
2010	140014	670	1075453	6113	6.23	1.10	1759.29	0.13	311
2011	142588	694	1147258	6249	6.05	1.11	1835.91	0.13	314.5
2012	112817	816	1213882	6388	6.72	1.28	1900.25	0.16	267
2013	107864	768	1263754	6530	6.08	1.18	1935.30	0.16	259
2014	102441	688	1331563	6675	5.20	1.03	1994.85	0.15	239
2015	111057	608	1412817	9531	4.30	0.68	1482.34	0.15	275
2016	144521	750	1502420	9798	4.99	0.77	1533.40	0.13	323

Source: JTI, 2016

The objectives of this research are to identify and quantify crash contributing factors through analyzing the necessary crash data, and to develop Crash Prediction Model (CPM) that link crash severities to the identified factors.

2. Literature Review

Researchers have constantly sought ways to improve traffic safety and gain better understanding to better predict crash likelihood under different crash contributing factors. Some researchers have specifically investigated crash contributing factors involving the geometric design features and design consistency of roads (Anderson et al., 1999; Montella, 2008). Anastasopoulos et al. (2012) investigated the pavement quality of roads as a crash contributing factor using the tobit regression model to predict accident rates per mile driven instead of frequency per unit time. Vogel and Bester (2005) studied the relationship between crash types and causes. They found that human factors contribute the most to traffic crashes with a percentage of 75.40 % of the total crashes, followed by environmental factors with a percentage of 14.5% and vehicle factors with a percentage of 10.20 %. Also, Spainhour et al. (2005) studied traffic crash fatality causes in Florida, USA. They found that human factors mainly driving under influence was the main factor which accounted for about 94.00 % of the total fatal crashes. Khan and Tehreem (2012) investigated the causes of road traffic crashes in Pakistan. They found that the main causes of traffic crashes were unskilled drivers, poor road conditions, use of cell phone while driving, and over loading. Jadaan et al. (2013) developed road fatality prediction model in Jordan using multiple linear regression. They found that weather, road pavement, road surface and light conditions do not have any major effect on fatal traffic crashes. Naghawi (2017) used the quasi induced exposure method to study young drivers' crashes in Jordan. She found that young drivers' crash risk increased under poor environmental conditions.

Many statistical methods have been used in crash modeling and prediction. Crash prediction models (CPMs) are very useful tools in traffic safety, with their capabilities to determine the relationship between frequency and/or severity of crashes and crash contributing factors. Early CPMs were generally based on linear regression assuming normality of the error term, constant variance for the residuals, and linear relationship between dependent and independent variables (Abbas et al., 2011; Obaidat & Ramadan, 2012). However many researchers illuminated the numerous problems with linear regression models (Miaou & Lum, 1993; Abdel-Aty and Radwan, 2000; Lord & Mannering, 2010) which have led to the adoption of more appropriate regression models such as Poisson Regression Models. Poisson Regression Models are based on a generalized linear regression and assume an exponential relationship between dependent and the independent variables (Eenin at al., 2007). One problem that always restricts the use of Poisson models is that the mean and the variance should be equal for the dependent variable (Winkelmann, 2003). To overcome this problem, the Negative Binomial (NB) or called Poisson gamma model has been investigated as an alternative to Poisson model given that it relaxes the condition of over dispersion (Abdel-Aty and Radwan, 2000).

3. Data Collection

The primary crash data needed for the development of the CPM were obtained from Jordan Traffic Institute (JTI) for the year 2014. The data included frequency and severity of crashes, also it included data on crash contributing factors.

4. Determination of Crash Contributing Factors

Determination of crash contributing factors is the most important step in the development of CPM. For the purpose of this study, crashes were categorized into severe and none severe crashes. Severe crashes are crashes that result in a fatality or an injury. Non severe crashes are crashes that don't result in a fatality or an injury. The collected crash data for the year 2014 included 102,441 crashes, 15.10 % of them were severe crashes. The collected crash data were organized into eight crash contributing factors. These factors included: age, age and gender, driver's faults, environmental conditions including road lighting, roadway surface and weather conditions, time including season, day and time of the day, speed, roadway defects and vehicle defects. Each of these crash contributing factors was divided into several crash contributing variables as will be discussed in the following sections.

Two steps were used for the determination of contributing factors that significantly affect crash severity in Jordan.

1. A preliminary descriptive analysis of the crash contributing factors for the year 2014 was done to identify and quantify factors affecting crash severity in Jordan. Then,

2. Negative Binomial Regression technique was used for the development of the CPM that link crash severities to the identified factors.

4.1 Step One: Preliminary Analysis

Table 2 through Table 9 show the frequency distribution of severe crashes for each crash contributing factor mentioned earlier.

4.1.1 Age Group

Driver's age is a demographic variable of great importance since it identifies groups of drivers with higher crash tendency. Drivers were grouped into six variables according to drivers age groups including (≤ 20, 21-30, 31-40, 41-50, 51-60 and > 60 years old) as summarized in Table 2. It can be seen that 20 years old or less age group were involved in the highest number of severe crashes with a percentage of 35.37 %. This might be explained by the immaturity of this age group which gives them the feeling of being unbeatable or what is called the "Superman Syndrome". Also it can be concluded that the percentage of severe crashes declines with age tell the age of less than 60, then it slightly increases among the elderly drivers of age 60 and more. Total number of crashes for each age group was not documented by the JTI.

Table 2. Crashes by Age

Age Group	Severe Crashes	Percent %
≤ 20	5475	35.37
21-30	3981	25.72
31-40	3132	20.24
41-50	1398	9.03
51-60	726	4.69
> 60	766	4.95

4.1.2 Age Group and Gender

Table 3 shows the analysis of severe crashes based on age and gender. It can be seen that males are more likely to get involved in crashes than females among all age groups. This might be explained by the fact that male drives more and are willing to take more risk than females. Also, the total number of crashes was not documented by the JTI.

Table 3. Crashes by Age and Gender

Age & Gender	Gender	Severe Crashes	Percent %
≤ 20	Male	3970	25.65
	Female	1505	9.72
21-30	Male	3173	20.50
	Female	808	5.22
31-40	Male	2446	15.80
	Female	686	4.43
41-50	Male	1037	6.70
	Female	361	2.33
51-60	Male	512	3.31
	Female	214	1.38
> 60	Male	552	3.57
	Female	214	1.38

4.1.3 Driver's Fault

Table 4 illustrates thirteen driver's faults variables that might contribute to severe traffic crashes. Drivers' faults included: tailgating, falling to take necessary precautions, using incorrect lane, priority false, improper backing, failing to yield, speeding, loss of control while driving, improper turn, running red light, driving in the opposite direction and wrong maneuver. The table also shows the total number of crashes, severe crashes and non severe crashes caused by each driver's fault. It was found that failing to take the necessary precautions resulted in the highest number of driver's fault crashes with a percentage of 27.89 % followed by tailgating with a percentage of 21.91 % followed by priority false with a percentage of 13.25 %. Theses faults resulted in 26.62 %, 2 4.92 % and13.92 % severe crashes for the three mentioned driver's faults respectively.

Table 4. Crashes by Driver's Fault

Driver's Fault	Total Number of Crashes	Percent %	Severe Crashes	Percent %	Non Severe Crashes	Percent %
Tailgating	22444	21.91	1041	6.29	21403	24.92
Falling to Take Necessary Precautions	28568	27.89	5698	34.44	22870	26.62
Using Incorrect Lane	9584	9.36	4342	26.25	5242	6.10
Priority False	13578	13.25	1621	9.80	11957	13.92
Improper Backing	10265	10.02	258	1.56	10007	11.65
Fail to Yield	2207	2.15	211	1.28	1996	2.32
Unsafe Speed	1189	1.16	306	1.85	883	1.03
Loss of Control while Driving	1041	1.02	362	2.19	679	0.79
Improper Turn	2062	2.01	637	3.85	1425	1.66
Running Red Light	617	0.60	87	0.53	530	0.62
Driving in the Opposite Direction	292	0.29	118	0.71	174	0.20
Wrong Maneuver	597	0.58	243	1.47	354	0.41
Other	9997	9.76	1619	9.79	8378	9.75

4.1.4 Environmental Conditions

Environmental conditions include road lighting conditions, road surface conditions and weather conditions. Road lighting conditions were divided into four variables: good lighting conditions for day light, fair lighting conditions for night with sufficient light, poor lighting conditions for night without sufficient light and other light conditions for dark, sunset and sunrise. Road surface conditions were divided into three conditions/variables: good surface condition indicating dry surface, fair surface condition indicating wet, mud and sandy surface and poor surface condition for snow, ice and oily surface. Weather conditions were divided into two variables: good weather conditions when no adverse conditions exist and poor weather conditions including fog, rain, snow, dust and hard wind. Table 5 shows frequency and percentage of crashes, severe crashes and non severe crashes related to environmental conditions. It was found that 77.07 % of the total severe crashes occurred under good lighting conditions, 95.88 % of the total severe crashes occurred under good road surface conditions and 96.52 % of all severe crashes have occurred under good weather conditions. These results indicate that the majority of crashes has occurred under good lighting, road surface and weather conditions. This is expected because good environmental condition is the dominant condition throughout the year in Jordan which is favorable conditions for speeding.

Table 5. Crashes under Different Environmental Conditions

Condition	Total Number of Crashes	Percent %	Severe Crashes	Percent %	Non Severe Crashes	Percent %
Lighting						
Good Condition	78954	77.07	11688	75.51	67266	77.35
Fair Conditions	13988	13.65	2010	12.99	11978	13.77
Poor Conditions	4425	4.32	856	5.53	3569	4.10
Other Conditions	5074	4.95	924	5.97	4150	4.77
Road Surface						
Good Condition	98221	95.88	14918	96.38	83303	95.79
Fair Conditions	3943	3.85	524	3.39	3419	3.93
Poor Conditions	277	0.27	36	0.23	241	0.28
Weather						
Good Condition	98871	96.52	15038	97.16	83833	96.40
Fair Conditions	3570	3.48	440	2.84	3130	3.60

4.1.5 Time

The year was divided into four seasons/variables: Spring (March through May), Summer (Jun through August), Fall (September through November) and Winter (December through February). The week was divided into the conventional seven days and the day was divided into four time periods including: morning peak (6am to 10am), day time (10am to 4pm), evening peak (4pm to 10pm) and night time (10pm to 6am). Table 6 shows the number of crashes, frequency and percentage, for each season, day and time of the day. It can be seen that 28.35 % of the severe crashes occurred during the summer months from June to August. While winter months witnessed the lowest number of severe crashes with a percentage of 21.48 %. Also the lowest number of severe crashes occurred during weekends specifically on Friday with a percentage of 13.33 %. The table also shows that almost 34.55 % of severe crashes occurred during day time then 32.77 % of severe crashes occurred during the evening peak. Finally, it can be concluded that the lowest number of severe crashes happen during morning peak with a percentage of 11.32 %.

Table 6. Crashes by Time

Time	Total Number of Crashes	Percent %	Severe Crashes	Percent %	Non Severe Crashes	Percent %
Season						
Spring	25709	25.10	3880	25.07	21829	25.10
Summer	28748	28.06	4388	28.35	24360	28.01
Fall	24161	23.59	3886	25.11	20275	23.31
Winter	23823	23.26	3324	21.48	20499	23.57
Day of the Week						
Sunday	16204	15.82	2317	14.97	13887	15.97
Monday	15271	14.91	2168	14.01	13208	15.19
Tuesday	14977	14.62	2100	13.57	12877	14.81
Wednesday	15975	15.59	2225	14.38	13750	15.81
Thursday	17039	16.63	2385	15.41	14654	16.85
Friday	8998	8.78	2063	13.33	6830	7.85
Saturday	13977	13.64	2220	14.34	11757	13.52

Time of the day						
6am – 10am	11404	11.13	1752	11.32	9652	11.10
10am - 4pm	42595	41.58	5348	34.55	37523	43.15
4pm – 10pm	37581	36.69	5072	32.77	32233	37.07
10pm -6am	10861	10.60	3306	21.36	7555	8.69

4.1.6 Speed

Speed was divided into eleven variables with 10 km/hr increments starting from 20 km/hr and ending with 120 km/hr. Table 7 shows the frequency and percentage of severe and non severe crashes for each speed limit increment. It can be seen that severe crashes increase with the increase in the speed limit up to 40 km/hr where it reaches the highest number of crashes, stay relatively high, then it declines noticeably for speed limits greater than 60 km/hr. This can be explained by the fact that higher speed limits are associated with high functional classification of roads in which higher design standards are implemented.

Table 7. Crashes by Speed Limit

Speed Limit (km/hr)	Total Number of Crashes	Percent %	Severe Crashes	Percent %	Non Severe Crashes	Percent %
20	2954	2.89	153	0.99	2801	3.22
30	4363	4.26	317	2.05	4046	4.65
40	40667	39.70	4529	29.26	36138	41.56
50	23462	22.90	2872	18.56	20590	23.68
60	21741	21.22	4137	26.73	17604	20.24
70	4845	4.73	1231	7.95	3614	4.16
80	3009	2.94	1392	8.99	1617	1.86
90	479	0.47	370	2.39	109	0.13
100	408	0.40	307	1.98	101	0.12
110	494	0.48	167	1.08	327	0.38
120	19	0.02	3	0.02	16	0.02

4.1.7 Roadway Defects

Roadway defects were divided into six variables including: defective shoulder area, defective roadway surface, signing obstructions, defective traffic control device, improper horizontal curve design and others. Table 8 illustrates the analysis of severe crashes for different roadway defects. The table didn't include total number of crashes as it was not documented by JTI. It can be seen that defective roadway surface contributed the most to severe crashes with a percentage of 5.01 % of the total number of severe crashes caused by defective roadway conditions.

Table 8. Crashes under Different Roadway conditions

Roadway Defects	Severe Crashes	Percent %
Defective Shoulder Area	6	0.16
Defective Roadway Surface	185	5.01
Signing Obstructions	7	0.19
Defective Traffic Control Device	69	1.87
Improper Horizontal Curve Design	29	0.79
Others	3394	91.98

4.1.8 Vehicle Defects

Vehicle defects were also analyzed as a crash contributing factor. Vehicle defects were divided into nine variables including: worn tires, lighting defect, steering defects, brake's defects, windshield defect, mirrors, direction indicators, mud pads and engine failure. Table 9 shows number of severe crashes under different vehicle defect variable. The table didn't include the total number of crashes since it was not documented by JTI. It was found that brake defects yielded the highest number of severe crashes with a percentage of 61.25 % of the total number of severe crashes then defective mirrors with a percentage of 28.05 % of the total number of severe crashes.

Table 9. Crashes under Different Vehicle Defects

Vehicle Defects	Severe Crashes	Percent %
Worn Tires	26	1.22
Lighting Defect	76	3.56
Steering Defects	10	0.47
Brake's Defects	1306	61.25
Windshield Defect	28	1.31
Mirrors	598	28.05
Direction Indicators	36	1.69
Mud Pads	17	0.80
Engine Failure	35	1.64

4.2 Step Two: Modeling of Crash Data

As mentioned earlier, both Poisson and Negative Binomial Regression methods are the most popular methods that are used to model count data. However, Poisson regression model requires that both the mean and the variance of the aggregated data are equal. When the data variance is larger than its mean, the data are over-dispersed, and in this case the negative binomial model is the suitable model for such data (Washington et al., 2011). To test our data against over-dispersion, a dispersion test suggested by Cameron and Trivedi (1998) was applied. The null hypothesis in this test is that both the mean and the variance for the data are equal (the mean is $E(Y) = \mu$ and the variance is $Var(Y) = \mu$ as well). This null hypothesis is tested against an alternative hypothesis where the variance is equal to $Var(Y) = \mu + c * f(\mu)$. In this equation, when the constant c is less than zero, it means under-dispersion and when the constant c is greater than zero, it means over-dispersion, and the function $f(\mu)$ is a linear function. This test was applied using "dispersiontest" function in R-statistic software (version 3.4.) package AER. The results of the test showed that the value of c was 5.215 which clearly indicate that the data is over-dispersed; therefore, the Negative Binomial Model will be applied using R-statistic software. The results from applying this test are shown in Table 11. The model contains intercept and the statistically significant crash contributing variables.

Table 11. Negative Binomial regression results

Coefficients	Estimate	Std. Error	z value	Sig.
(Intercept)	9.17312	0.19335	47.442	2E-16
Age	-0.45145	0.07056	-6.398	1.57E-10
Age-Male	-0.52019	0.0706	-7.368	1.73E-13
Age-Female	-0.73457	0.07094	-10.355	2E-16
Tailgating	2.22518	0.55581	4.003	0.0000624
Priority False	1.78232	0.5555	3.208	0.00133
Improper Backing	3.62016	0.55843	6.483	9.01E-11
Fail to Yield	3.82126	0.5592	6.833	8.29E-12
Unsafe Speed	3.44954	0.55788	6.183	6.28E-10
Loss of Control while Driving	3.28148	0.55743	5.887	3.94E-09
Improper Turn	2.71635	0.55636	4.882	0.00000105
Driving in the Opposite Direction	4.40244	0.56253	7.826	5.03E-15
Wrong Maneuver	3.68006	0.55864	6.587	4.47E-11
Turnover	2.25344	0.55584	4.054	0.0000503
Lighting	-0.67381	0.162	-4.159	0.0000319
Road Surface	-1.1047	0.16237	-6.804	1.02E-11
Weather	-0.55596	0.26007	-2.138	0.03254
Day of the Week	-0.27313	0.05859	-4.662	0.00000313

Time of the day	-0.2754	0.11482	-2.399	0.01646
Brake's Defects	4.64052	0.56455	8.22	2E-16
Mirrors	2.77953	0.55645	4.995	0.000000588

It can be seen that 20 variables were found to be statistically significant and impact severe crashes. The positive sign for a parameter indicates that severe crashes will increase as the value for the variables related to that parameter increase. The negative sign for a parameter indicates that severe crashes will decrease as the value for the variable related to that parameter increase. Therefore, the results in Table 11 indicated that severe crashes will decrease as the age of both male and female drivers increase. This can be attributed to the increase in drivers' experience as the driver's age increase. However, the parameter values indicate that severe crashes decrease at a higher rate as age of females increase than that of males. The same relationship is obtained between severity of crashes and both the environment and the time factors. First, severity of crashes decreases as road lighting conditions gets better. This can be attributed to the fact that drivers are more cautious in driving under poor road lighting conditions. The same conclusion can be applied for the relation between severity of crashes and road surface condition, where severity of crashes under good road surface condition is more than that under bad road surface condition. In addition to the environmental factors, the results in Table 11 indicate that severity of crashes will be higher during weekdays than at weekends, and in the morning than in the evening. However, the small value of the parameters for these two variables indicates that these two factors do not have high contribution to the severity of crashes. On the other hand, the results in Table 11 indicates that the number of crashes increase as drivers have faults in driving. Finally, mirror and brake deficits were found to be the only factors among all possible vehicle deficits that contribute to severe crashes. These findings are in agreement with the descriptive analysis of the crash contributing factors except that it was found that speed and roadway defects had no statistical significant effect on CPM.

5. Summary

The objectives of this research are to identify and quantify factors affecting crash severity in Jordan through analyzing necessary crash data, and to develop a crash prediction model that relates crash severity to the identified factors. The data needed were obtained from Jordan Traffic Institute (JTI) for the year 2014. The data included number and severity of crashes for each crash contributing factor. The collected crash data were organized into nine crash contributing categories. These categories included: driver's edge, driver's edge and gender, driver's fault, crash type, time, speed, environment factors, roadway defects and vehicle defects. Two steps were used for the determination of contributing factors that significantly affect crash severity. First a preliminary descriptive analysis of the crash contributing factors was done to identify and quantify factors affecting crash severity. Then, the Negative Binomial Regression model was developed using R-statistic software. The results indicated that the model contained 20 variables that significantly impact severe crashes in Jordan. Among the general finding, it was found severe crashes decreased significantly as the age of both male and female drivers increased. They significantly decreased as the environmental conditions improved. In addition, sever crashes were significantly higher during weekdays than weekends and in the morning than in the evening. The results also indicated that sever crashes significantly increased as drivers have faults while driving. In addition, mirror and brake deficits were found to be the only factors among all possible vehicle deficits factors that contributed significantly to severe crashes. Finally, it was found that the results of the Negative Binomial Regression model are in agreement with the descriptive analysis of the crash contributing factors.

References

Abbas, A., Hefny. A., & Abu-Zidan. F. (2011). Seatbelts and Road Traffic Collision Injuries. *World Journal of Emergency Surgery, 6*(18). Retrieved from https://wjes.biomedcentral.com/articles/10.1186/1749-7922-6-18

Abdel-Aty, M. A., & Radwan, A. E. (2000). Modeling Traffic Accidents Occurrence and Involvement. *Accident Analysis and Prevention, 32,* 633-642.

Anastasopoulos, P. C., Mannering, F. L., Shankar, V. N., & Haddock, J. E. (2012). A Study of Factors Affecting Highway Accident Rates Using Random-Parameters Tobit Model. *Accident Analysis and Prevention, 45*, 628-633.

Anderson, I. B., Bauer, K., Harwood, D. W., & Fatzatrick, K. (1999). Relationship to Safety of Geometric Design Consistency Measures for Rural Two-Lane Highways. *Transportation Research Record, 1658*, 43-51.

Cameron, A. C., & Trivedi, P. K. (1998). Regression Analysis of Count Data. Cambridge University Press.

Cambridge, UK.

Eenink, R., Reuring, M., Elvik, R., Cardoso, J., Wichert, S., & Stefan, C. (2007). Accident Prediction Models and Road Safety Impact Assessment: Recommendations for using these tools. Result of the pilot studies. RI-SWOV-WP2-R4-V2-Results. RIPCOD-ISEREST Deliverable D2. BAST. Retrieved from http://ripcord.bast.de/pdf/RIPCORD-ISEREST-Deliverable-D2-Final.pdf

Global Finance. (2016). Jordan GDP and Economic Data. Country Report 2016 - Includes Jordan real Gross Domestic Product growth rate, with latest forecasts and historical data, GDP per capita, GDP composition and breakdown by sector. Retrieved from https://www.gfmag.com/global-data/country-data/jordan-gdp-country-report

Jadaan, K., AL-Hyari, I., Naghawi, H., Ammourah, R., & Al Nabulsi, Z. (2013). Traffic Safety in Jordan: Magnitude, Cost and Potential Countermeasures. *Journal of Traffic and Logistics Engineering, 1*(1), 54-57.

Jordan Traffic Institute (JTI) Traffic Accident statistics reports for years 2004-2016. Ministry of Interior, Jordan. Retrieved from: http://www.psd.gov.jo/images/jti/images/411.pdf

Khan, A. M., & Tehreem, A. (2012). Causes of Road Accidents in Pakistan. *Journal of Asian Development Studies, 1*(1).

Lord, D., & Mannering, F. (2010). The Statistical Analysis of Crash-Frequency Data: A Review and Assessment of Methodological Alternatives. *Transportation Research Part A: Policy and Practice, 44*(5), 291-305.

Miaou, S. P., & Lum, H. (1993). Modeling Vehicle Accidents and Highway Geometric Design Relationship. *Accident Analysis and Prevention, 25,* 689-709.

Montella, A. (2008). Crash Prediction Models for Rural Motorways. *Transportation Research Record, 2083*, 180-189.

Murray, C., & Lopez A. The Global Burden of Disease. (1996). *Cambridge, MA: Harvard University Press, 1.*

Naghawi, H. (2017). Young Drivers' Safety in Jordan. Transportation Research Board 96th Annual Meeting Transportation Research Board. Washington, DC.

Obaidat, M., & Ramadan, T. (2012). Traffic Accidents at Hazardous Locations of Urban Roads. *Jordan Journal of Civil Engineering, 6*(4).

Spainhour, L., Brill, D., Sobanjo, J., Wekezer, J., & Mtenga, P. (2005). Evaluation of Traffic Crash Fatality Causes and Effects. Summary of Final Report, BD050, Florida. Retrieved from http://www.fdot.gov/safety/4-Reports/Bike-Ped/FDOT_BD050.pdf

Vogel, L., & Bester, C. J. (2005). A Relationship between Accident Types and Causes. *Department of Civil Engineering, University of Stellenbosch*.

Washington, S., Karlaftis, M., & Mannering, F. (2011). Statistical and Econometric Methods for Transportation Data Analysis. Chapman and Hall/CRC, Boca Raton, FL, Second edition.

Winkelmann, R. (2003). Econometric Analysis of Count Data, 4^{th} ed. Springer Verlag, Heidelberg.

World Health Organization (WHO). (2014). *Violence and Injury Prevention.* Retrieved from http://www.who.int/topics/injuries_traffic/en/