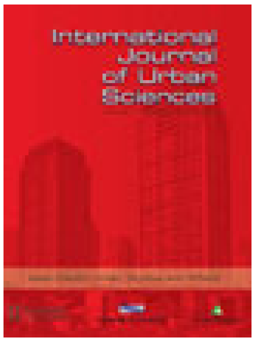

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Modelling single-vehicle, single-rider motorcycle crash injury severity: an ordinal logistic regression approach

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ABSTRACT

Motorcycles represent an increasing proportion of traffic fatalities in the United States, accounting for more than 12.7% of the total traffic casualties within 2005–2014. Specifically, in North Carolina, motorcycles comprise less than 1% of vehicles involved in crashes but account for more than 7% of total fatalities, representing a top state in the United States. This study tries to investigate the motorcycle crashes in North Carolina more in depth. In doing so, five years' (2009–2013) worth of crash data was obtained from the Federal Highway Administration's Highway Safety Information System database. A partial proportional odds (PPO) logistic regression model was developed to examine the influence of the explanatory variable on the ordered dependent variable, that is, injury severity. Moreover, two other popular ordered-response models, that is, proportional odds and non-proportional odds models, as well as one similar unordered-response model, that is, multinomial logit model, were also developed to evaluate their performances compared to the PPO model. Older riders, DUI riding, not wearing helmets, crashes during summer and weekends, darkness, crashes with fixed objects, reckless riding, and speeding were found to increase the severity of injuries. In contrast, younger riders, winter season, adverse weather condition, and wet surface were associated with lower injury severities. Furthermore, crashes in rural areas, overturn/rollover, and crashes happened while negotiating a curve showed fluctuating effects of injury severity. According to two information criteria calculated for all three developed models fitted to the same data, the PPO model was found to outperform the other models and provide more reliable results. Based on the obtained average direct pseudo-elasticities, this study determines the effect of the various identified variables and develops several safety countermeasures as a resource for policy-makers to prevent or mitigate the severity of motorcycle crashes in North Carolina.

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Single-rider motorcycle crash; safety implications; partial proportional odds (PPO) model; model comparison; highway safety information system (HSIS) database

1. Introduction

Motorcycles represent an increasing proportion of traffic fatalities in the United States. In a nationwide scale, per a query of 10 years (2005–2014) of crash data from the Fatality Analysis Reporting System database, an average of 4573 fatalities occurred each year

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involving motorcyclists, accounting for more than 12.7% of the total traffic casualties for that period (National Highway Traffic Safety Administration [NHTSA], 2016). The most recent data from the NHTSA revealed that in 2013 and per vehicle mile travelled, the national fatality rate associated with motorcycles was 26 times that of passenger cars (NHTSA, 2015). In that particular year, the state of North Carolina was ranked fourth in the nation in terms of total motorcycle rider fatalities. With many possible factors contributing to motorcycle collisions (e.g. infrastructure and environmental factors, motorcycle rider factors, and motorcycle factors), it is incumbent upon traffic safety researchers and policy-makers to get a clear and deeper understanding of the most significant contributing factors. This effort is most appropriately accomplished through further analysis and using proper tools to develop more effective safety countermeasures.

Many studies have already addressed the severity of crashes involved motorcycles. Jimenez, Bocarejo, Zarama, and Yerpez (2015) developed accident prototypical scenarios to investigate 400 police crash records to find patterns in motorcycle-involved crashes in Colombia. These crashes fell into three categories: solo motorcycle crashes, motorcycle–vehicle crashes, and motorcycle–pedestrian crashes. A lack of experience, wider roads with higher speed limits, and poor infrastructure maintenance were found to increase the likelihood of motorcycle-involved crashes. In another study, Maistros, Schneider, and Savolainen (2014) conducted an analysis to compare contributing factors between alcohol-related single-vehicle motorcycle and car crashes. In developing mixed logit models for motorcycle riders and passenger car drivers, it was found that the presence of horizontal curves, speeding, and neglecting helmet and seatbelt use increased the severity of motorcycle crashes. Shaheed and Gkritza (2014) found that roadway surface conditions, lighting conditions, speed limit, and the use of a helmet significantly influenced crash severity outcomes. Haque, Chin, and Debnath (2012) employed a log-linear model to evaluate multi-vehicle motorcycle crashes in Singapore and found that lighting and road surface conditions affect the probability of motorcycle-involved crashes. The results of a study conducted by de Rome and Senserrick (2011) revealed that driver age, roadway surface conditions, and horizontal curves contributed significantly to motorcycle crash severity. Geedipally, Lord, and Dhavala (2012) employed a multinomial logistic regression model to investigate various contributing factors associated with motorcycle crashes in Texas. Based on the obtained results, factors such as alcohol, gender, lighting conditions, and the presence of horizontal and vertical curves significantly affected the severity of motorcycle crashes in urban areas. Teoh and Campbell (2010) explored a strong relationship between motorcycle type and motorcycle rider fatalities. Houston (2007) showed that motorcycle helmet laws mitigate the rates of young motorcyclist fatalities by 31%. Schneider, Savolainen, and Moore (2010) evaluated the effect of horizontal curvatures on single-vehicle motorcycle crashes on rural two-lane highways using a negative binomial model. Based on their results, a short radius and insufficient length of a curve significantly increased the frequency of motorcycle crashes.

In the motorcycle crash study domain, the nature of the type of injury is highly associated with the number of vehicles involved. In other words, several past studies (Geedipally et al., 2012; Haque et al., 2012; Ivan, 2004; Jonsson, Ivan, & Zhang, 2007; Savolainen & Mannering, 2007; Yau, 2004) asserted that separating motorcycle crash types into single- and multi-vehicle crashes is advisable due to the different nature of crashes and their causes. Moreover, according to previous studies (Savolainen & Mannering, 2007;

Shaheed & Gkritza, 2014), multi-vehicle motorcycle crashes tend to be less severe than single-vehicle crashes, which is the crash type upon which this paper focuses. The presence of other pillion passengers in addition to the rider is another factor that will potentially affect the injury severity of a crash. This study intends to develop a model for single-vehicle, single-rider motorcycle crash injury severity to gain more reliable, additional insight into the main cause of serious injuries to motorcyclists. Based on the above-mentioned arguments, the reason for setting such a limitation is to offset the possible effects that the presence of other vehicles and riders have on motorcycle riders' behaviour and the resulting change in the injury outcome. More importantly, such segmentation of motorcycle crashes increases the homogeneity of the crash data and increases the reliability of the obtained findings.

2. Data

Five years (2009–2013) of crash records in North Carolina, obtained from the Federal Highway Administration's Highway Safety Information System (HSIS), were used. The HSIS database is composed of four different sub-files, including Accident, Occupant, Vehicle, and Roadway. Depending on the sub-files being linked together, variables such as Case Number, Vehicle Number, County, Route Number, and Milepost might be of use. For a complete description of the linking process, readers are encouraged to refer to the HSIS North Carolina Guidebook (Nujjetty, Mohamedshah, & Council, 2014). Given the scope of this study, only those single-vehicle motorcycle crashes without any riders other than the operator (6545 records) were selected for final analysis.

The HSIS database uses the five-level injury severity of (1) fatality, (2) incapacitating injury (A-injury), (3) non-incapacitating injury (B-injury), (4) possible injury (C-injury), and (5) no injury. Based on this categorization, 234 (3.6%) fatal crashes, 562 (8.6%) incapacitating injury, 3451 (52.7%) non-incapacitating injury, 1545 (23.6%) possible injury, and 753 (11.5%) no injury crashes were found to compose the crash dataset. These categorizations, along with the variables considered in this study, are cross-tabulated and presented in Table 1.

3. Method

3.1. Econometric model

There is an extensive body of literature on the application of statistical modelling in transportation science (e.g. Baireddy, Pour-Rouholamin, Zhou, & Qi, 2017; Christensen, Sharifi, & Chen, 2013; Ghasemi, Jalayer, Pour-Rouholamin, Nowak, & Zhou, 2016; Pour-Rouholamin & Zhou, 2016c; Shafabakhsh, Pour-Rouholamin, & Motamedi, 2012; Sharifi, Stuart, Christensen, & Chen, 2015; Soltani-Sobh, Heaslip, Bosworth, & Barnes, 2015; Soltani-Sobh, Heaslip, Bosworth, Barnes, & Yook, 2016). Over the past years, numerous disaggregate modelling approaches have been employed to quantify the effect of several contributing factors on various levels of injury severity. Given the ordered nature of the injury severity in crashes (representing an ordinal outcome), these methodological approaches generally fall into two main categories (based on whether this nature is considered or not): ordered-response models and unordered-response models.

Table 1. Distribution of injury severity by explanatory variables.

Explanatory variable	Fatality		A-injury		B-injury		C-injury		PDO		Total
Total	234	3.6%	562	8.6%	3451	52.7%	1545	23.6%	753	11.5%	6545
Motorcyclist characteristics											
Age											
Younger rider (Less than 24)	25	1.9%	102	7.9%	686	52.8%	319	24.6%	167	12.9%	1299
Middle-aged rider (25 to 64)	185	3.8%	423	8.6%	2598	52.8%	1158	23.5%	560	11.4%	4924
Older rider (65 and over)	24	7.5%	37	11.5%	167	51.9%	68	21.1%	26	8.1%	322
Gender											
Male	221	3.7%	528	8.8%	3157	52.5%	1395	23.2%	716	11.9%	6017
Female	13	2.5%	34	6.4%	294	55.7%	150	28.4%	37	7.0%	528
DUI driving?											
No	154	2.7%	431	7.6%	3003	52.6%	1412	24.8%	704	12.3%	5704
Yes	80	9.5%	131	15.6%	448	53.3%	133	15.8%	49	5.8%	841
Helmet used?											
Yes	213	3.5%	503	8.3%	3193	52.6%	1444	23.8%	714	11.8%	6067
No	21	4.4%	59	12.3%	258	54.0%	101	21.1%	39	8.2%	478
Temporal variables											
Season											
Spring	73	3.6%	165	8.2%	1067	52.8%	495	24.5%	221	10.9%	2021
Summer	88	3.8%	228	9.9%	1284	55.9%	471	20.5%	225	9.8%	2296
Autumn	59	3.6%	132	8.2%	797	49.3%	409	25.3%	220	13.6%	1617
Winter	14	2.3%	37	6.1%	303	49.6%	170	27.8%	87	14.2%	611
Day of week											
Weekday	121	3.2%	292	7.8%	1944	51.8%	924	24.6%	469	12.5%	3750
Weekend	113	4.0%	270	9.7%	1507	53.9%	621	22.2%	284	10.2%	2795
Time of day											
Morning	39	3.6%	79	7.3%	542	50.4%	267	24.8%	148	13.8%	1075
Afternoon	73	2.5%	248	8.4%	1586	54.0%	711	24.2%	319	10.9%	2937
Evening	85	4.3%	179	9.1%	1031	52.3%	454	23.0%	221	11.2%	1970
Night	37	6.6%	56	9.9%	292	51.9%	113	20.1%	65	11.5%	563
Crash variables											
Type of setting											
Urban	34	2.5%	49	3.5%	763	55.1%	376	27.1%	163	11.8%	1385
Rural	200	3.9%	513	9.9%	2688	52.1%	1169	22.7%	590	11.4%	5160
Weather condition											
Clean/cloudy	231	3.7%	551	8.7%	3351	53.0%	1479	23.4%	716	11.3%	6328
Adverse	3	1.4%	11	5.1%	100	46.1%	66	30.4%	37	17.1%	217
Surface condition											
Dry	227	3.7%	542	8.9%	3220	53.0%	1413	23.2%	679	11.2%	6081
Wet	5	1.4%	17	4.7%	184	50.8%	97	26.8%	59	16.3%	362
Lighting condition											
Daylight	137	3.0%	368	8.1%	2444	53.7%	1104	24.3%	499	11.0%	4552
Dawn/dusk	4	1.6%	24	9.5%	131	51.8%	53	20.9%	41	16.2%	253
Dark – lit	21	6.4%	16	4.9%	168	51.2%	88	26.8%	35	10.7%	328
Dark – not lit	72	5.1%	154	11.0%	700	50.0%	298	21.3%	177	12.6%	1401
Intersection related?											
Yes	21	3.0%	43	6.1%	375	53.1%	180	25.5%	87	12.3%	706
No	213	3.6%	519	8.9%	3076	52.7%	1365	23.4%	666	11.4%	5839
Accident type											
Animal	9	1.4%	37	5.9%	302	47.9%	148	23.5%	135	21.4%	631
Fixed-object	129	7.5%	209	12.1%	848	49.0%	375	21.7%	169	9.8%	1730
Overturn/rollover	66	2.4%	240	8.6%	1568	56.1%	652	23.3%	267	9.6%	2793
Run-off-the-road	27	3.4%	45	5.7%	403	51.4%	214	27.3%	95	12.1%	784
Contributing factor											
Overcorrected/oversteered	9	2.0%	26	5.8%	252	55.9%	118	26.2%	46	10.2%	451
Reckless	50	4.0%	125	9.9%	713	56.4%	268	21.2%	108	8.5%	1264
Speeding	89	5.7%	183	11.6%	793	50.4%	338	21.5%	170	10.8%	1573
Roadway functional classification											
Arterial	66	2.8%	148	6.3%	1271	54.4%	582	24.9%	271	11.6%	2338
Collector	79	3.7%	209	9.8%	1067	50.0%	514	24.1%	266	12.5%	2135
Local	89	4.3%	205	9.9%	1113	53.7%	449	21.7%	216	10.4%	2072
Locality											

(*Continued*)

Table 1. Continued.

Explanatory variable	Fatality		A-injury		B-injury		C-injury		PDO		Total
Commercial	22	1.9%	44	3.8%	646	56.0%	311	27.0%	130	11.3%	1153
Farms, woods, pastures	157	4.0%	393	9.9%	2035	51.2%	908	22.9%	478	12.0%	3971
Residential	53	3.9%	125	9.1%	740	53.9%	314	22.9%	142	10.3%	1374
Left shoulder width											
No shoulder	40	3.2%	82	6.5%	663	52.9%	322	25.7%	147	11.7%	1254
1–3 ft	30	3.8%	78	10.0%	406	52.0%	180	23.0%	87	11.1%	781
4–6 ft	125	3.8%	315	9.6%	1704	52.1%	746	22.8%	382	11.7%	3272
7–9 ft	12	3.1%	25	6.6%	211	55.4%	89	23.4%	44	11.5%	381
10–13 ft	25	3.4%	55	7.5%	394	53.5%	184	25.0%	79	10.7%	737
Over 14 ft	2	1.7%	7	5.8%	73	60.8%	24	20.0%	14	11.7%	120
Right shoulder width											
No shoulder	39	3.2%	81	6.6%	646	52.9%	310	25.4%	146	11.9%	1222
1–3 ft	31	4.0%	76	9.8%	399	51.4%	180	23.2%	90	11.6%	776
4–6 ft	126	3.9%	315	9.7%	1690	51.9%	746	22.9%	377	11.6%	3254
7–9 ft	12	3.2%	25	6.6%	208	55.2%	89	23.6%	43	11.4%	377
10–13 ft	22	2.8%	54	7.0%	427	55.2%	188	24.3%	83	10.7%	774
Over 14 ft	4	2.8%	11	7.7%	81	57.0%	32	22.5%	14	9.9%	142
Presence of median?											
Yes	39	3.2%	65	5.4%	663	54.7%	310	25.6%	135	11.1%	1212
No	195	3.7%	497	9.3%	2788	52.3%	1235	23.2%	618	11.6%	5333
Number of lanes											
Two	188	3.7%	486	9.6%	2629	52.1%	1162	23.0%	579	11.5%	5044
More than two	46	3.1%	76	5.1%	822	54.8%	383	25.5%	174	11.6%	1501
Roadway characteristic											
Straight	70	2.2%	193	6.0%	1752	54.5%	838	26.1%	362	11.3%	3215
Curve	164	5.0%	369	11.2%	1694	51.5%	706	21.5%	356	10.8%	3289

In this study, the dependent variable, the severity given a motorcycle crash has happened, can be modelled by considering the ordered nature of crash severity and using ordered-response models. In these models, the dependent variable retains an ordinal structure with at least three categories that have been arranged based on their importance in defining the outcome. For instance, in severity analysis using these models, fatality is given the highest priority due to its severe nature, and the other severity levels should be sorted in descending order; that is, incapacitating injury, non-incapacitating injury, possible injury, and no injury. There are three ordered-response models that have previously been used by various studies, called proportional odds (PO) model, non-proportional odds (NPO) model, and partial proportional odds (PPO) model.

The difference between these three models lies in the approach to handling parallel line assumption. According to this assumption in ordered-response models, which belongs to ordinal odds, the effect of the explanatory variables entered in the model is assumed to be constant across each ordinal category, and the only difference between the regression lines is the cut-off point for the threshold. This causes regression lines that are parallel to each other. If this assumption holds, the PO model is suggested. In reality, however, this assumption is sometimes relaxed (Boes & Winkelmann, 2006), which necessitates the use of NPO and PPO models. In the NPO model, it is assumed that all the explanatory variables do vary across equations for different categories of the dependent variable. However, the adoption of this assumption may, in turn, result in an unnecessary increase in the number of calculated parameter estimates (i.e. coefficients), as not all the explanatory variables in the model will violate the parallel line assumption. This consideration led to the emergence of PPO model that accounts for the fact that not every single explanatory variable will violate the parallel line assumption.

As mentioned earlier, the dependent variable in this study (i.e. crash severity) is categorized into five groups. Given this, let j denote the crash severity level (1 = no injury, 2 = possible injury; 3 = non-incapacitating injury; 4 = incapacitating injury; 5 = fatality) and let J represent the number of severity levels (here $J = 5$), where $j = 1, 2, \ldots, J - 1$. Table 2 shows the three models, their equations, how they differ from each other, and the description of parameters.

Before fitting the model, it is necessary to test whether this assumption is valid. There are several tests to examine the validity of this assumption, such as the likelihood ratio test, the Wolfe Gould test, and the Brant test. In this study, a Brant (1990) test is proposed before model estimation to determine whether any of the variables violates this assumption. This test estimates the coefficients for the underlying binary logistic regressions and examines the equality of all parameter estimates for individual variables using a chi-square statistic. If the test statistic is statistically significant, the parallel line assumption is violated for that particular variable.

3.2. Elasticity

The interpretation of the results from ordered-response models needs more attention, as the sign and value of the βs do not always determine the direction and magnitude of the effect of the intermediate levels for crash severity (Kaplan & Prato, 2012). In other words, the estimated coefficients are not sufficient to determine the net change in the outcome probabilities, given the change in the explanatory variables. The reason is that the marginal effect of one specific variable depends on the parameter estimates of all other variables in the model (Khorashadi, Niemeier, Shankar, & Mannering, 2005). Therefore, elasticities can be used for interpretation purposes instead of single coefficients. It should be noted that elasticities are applicable to continuous variables, whereas – given the nature of explanatory variables in this study that are dummy variables taking the value of 0 or 1 – direct pseudo-elasticities can instead be used for each injury severity and each crash. This measure is calculated as the change in the percentage of crash severity probability when

Table 2. Equations of the PO, NPO, and PPO models.

Model	Equation
PO	$\Pr(Y_i > j) = \dfrac{\exp(X_i\beta - \alpha_j)}{1 + [\exp(X_i\beta - \alpha_j)]}$
NPO	$\Pr(Y_i > j) = \dfrac{\exp(X_i\beta_j - \alpha_j)}{1 + [\exp(X_i\beta_j - \alpha_j)]}$
PPO	$\Pr(Y_i > j) = \dfrac{\exp(X_{1i}\beta_1 + X_{2i}\beta_2 - \alpha_j)}{1 + [\exp(X_{1i}\beta_1 + X_{2i}\beta_2 - \alpha_j)]}$
Description of parameters	
Y_i	Observed severity for crash i
β	Vector of parameter estimations in PO model, holding parallel line assumption
β_j	Vector of parameter estimations in NPO model, relaxing parallel line assumption
β_1	Vector of parameter estimations in PPO model, holding parallel line assumption
β_2	Vector of parameter estimations in PPO model, relaxing parallel line assumption
X_i	Vector of explanatory variables
X_{1i}	Vector of explanatory variables in PPO model, holding parallel line assumption
X_{2i}	Vector of explanatory variables in PPO model, relaxing parallel line assumption
α_j	Cut-off term for the threshold in the model

the dummy variable is switched from 0 to 1, or vice versa. Direct pseudo-elasticity can be computed as (Pour-Rouholamin & Jalayer, 2016):

$$E_{x_{jnk}}^{\Pr(Y_i>j)} = \frac{\Pr(Y_i > j)[\text{Given } x_{jnk} = 1] - \Pr(Y_i > j)[\text{Given } x_{jnk} = 0]}{\Pr(Y_i > j)[\text{Given } x_{jnk} = 0]},$$

where $\Pr(Y_i > j)$ is defined by equations in Table 2 (whichever applies) and x_{jnk} is the k-th explanatory variable associated with the injury severity j for the individual crash n. The average direct pseudo-elasticities can then be calculated for each injury severity to represent the whole dataset (Kim, Ulfarsson, Shankar, & Mannering, 2010).

4. Results and discussion

Before presenting the model estimation results using identified ordered-response models, it is important to check the parallel line assumption to justify the choice among PO, NPO, and PPO models. In doing so, a Brant test was conducted for both the entire model, as well as for every single parameter separately. The results of this test indicated the violation of this assumption for some variables, which necessitates developing a PPO model. Using the PPO model, the effect of various explanatory variables presented in Table 1 is analysed, and the corresponding parameter estimates obtained through the maximum likelihood estimation method as well as average direct pseudo-elasticities are listed in Tables 3 and 4, respectively. As can be seen from Table 3, 17 categories of explanatory variables were found to have a significant effect on the injury severity of drivers in single-vehicle, single-rider motorcycle crashes in North Carolina. Among these 17 categories, 6 violated parallel line assumption, showing a varying effect on different levels of severity. Therefore, and per the PPO formulation, these 6 violating parameters have different parameter estimates (or coefficients) across injury severity levels, while the remaining 11 variables have the same parameter estimates across all severity levels and for various thresholds, showing a linear effect (either increasing or decreasing the severity). It is worth noting that to make a more parsimonious model, explanatory variables with a p-value of less than 0.10 on at least one of the thresholds were kept in the final model. The Wald chi-square statistic of 556.38 with 35 degrees of freedom, which is substantially larger than the respective chi-square values at any reasonable confidence level, demonstrates that the presence of exogenous variables significantly improves the quality of the model's estimation.

4.1. Model comparison

Two commonly used information criteria, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), were used to compare the models. At first, these values for all three parsimonious models (PPO, NPO, and PO) are calculated and presented in Table 5. A comparison of the calculated values for both AIC and BIC for all these three models shows that the PPO models yield lower values for both information criteria, outperforming the other two models and providing a better fit.

It was also tried to validate the ordinal assumption of the crash injury severity as the next step. In doing so, the crash data were used to develop the multinomial logit model (MNL). The MNL model is very similar to the PPO model except it does not consider

Table 3. Parameter estimates (coefficients) for various thresholds for PPO model.

Explanatory variable	Threshold 1	Threshold 2	Threshold 3	Threshold 4
Motorcyclist characteristics				
Age				
Younger rider (less than 24)	−0.123**	−0.123**	−0.123**	−0.123**
Older rider (65 and over)	0.402***	0.402***	0.402***	0.402***
DUI driving?				
Yes†	0.727***	0.710***	1.049***	1.289***
Helmet used?				
No	0.206**	0.206**	0.206**	0.206**
Temporal variables				
Season				
Summer	0.238***	0.238***	0.238***	0.238***
Winter	−0.221***	−0.221***	−0.221***	−0.221***
Day of week				
Weekend	0.127***	0.127***	0.127***	0.127***
Crash variables				
Type of setting				
Rural†	−0.250**	−0.031	0.489***	−0.066
Weather condition				
Adverse	−0.292*	−0.292*	−0.292*	−0.292*
Surface condition				
Wet	−0.307**	−0.307**	−0.307**	−0.307**
Lighting condition				
Dark – lit	0.023*	0.023*	0.023*	0.023*
Dark – not Lit	0.144***	0.144***	0.144***	0.144***
Accident type				
Fixed-object†	0.499***	0.241***	0.535***	0.962***
Overturn/rollover†	0.553***	0.245***	−0.002	−0.052
Contributing factor				
Reckless	0.313**	0.313**	0.313**	0.313**
Speeding†	0.144	0.204***	0.516***	0.712***
Roadway characteristic				
Curve†	−0.035	0.099*	0.410***	0.453***
Cut point	1.655***	0.128*	−3.345***	−4.594***
Number of observations	6545			
Wald χ^2 (35)	556.38			
Log likelihood at constant	−8226.70			
Log likelihood at convergence	−7937.57			
AIC	15,953.13			
BIC	16,217.81			

***Statistically significant at $\alpha = 0.01$.
**Statistically significant at $\alpha = 0.05$.
*Statistically significant at $\alpha = 0.10$.
†Explanatory variable violating parallel line assumption.

the injury severity an ordinal outcome. AIC and BIC values for the MNL model were also calculated and presented in the same table (Table 5). As can be seen, PPO also yields lower values for both AIC and BIC criteria compared to the MNL model, meaning that the PPO (an ordered model) outperforms the unordered (MNL) model and provides a better fit to our data.

4.2. Motorcyclist characteristics

The motorcycle rider's age is classified into three groups: younger rider (less than 24), middle-aged rider (between 25 and 64), and older rider (65 and over). Having the middle-aged rider as the reference (base) category, the study results showed the significant effect of different levels of age on the injury outcome of the motorcycle rider. In other

Table 4. Average direct pseudo-elasticities for various severity levels.

Explanatory variable	PDO	C-injury	B-injury	A-injury	Fatality
Motorcyclist characteristics					
Age					
Younger rider (less than 24)	10.9%	6.6%	−2.8%	−10.4%	−11.8%
Older rider (65 and over)	−35.6%	−21.5%	9.2%	33.9%	38.8%
DUI driving?					
Yes†	−64.4%	−37.2%	9.7%	79.8%	124.3%
Helmet used?					
No	−18.2%	−11.0%	4.7%	17.4%	19.9%
Temporal variables					
Season					
Summer	−21.1%	−12.7%	5.5%	20.0%	22.9%
Winter	19.6%	11.8%	−5.1%	−18.6%	−21.3%
Day of week					
Weekend	−11.2%	−6.8%	2.9%	10.7%	12.2%
Crash variables					
Type of setting					
Rural†	22.1%	−7.5%	−10.8%	61.2%	−6.3%
Weather condition					
Adverse	25.8%	15.6%	−6.7%	−24.6%	−28.1%
Surface condition					
Wet	27.2%	16.4%	−7.0%	−25.9%	−29.6%
Lighting condition					
Dark – lit	−2.0%	−1.2%	0.5%	1.9%	2.2%
Dark – not lit	−12.8%	−7.7%	3.3%	12.2%	13.9%
Accident type					
Fixed-object†	−44.2%	−2.1%	−0.2%	29.8%	92.7%
Overturn/rollover †	−48.9%	−0.2%	10.4%	1.6%	−5.0%
Contributing factor					
Reckless	−27.7%	−16.7%	7.2%	26.4%	30.2%
Speeding†	−12.8%	−13.4%	−1.4%	36.5%	68.7%
Roadway characteristic					
Curve†	3.1%	−10.9%	−3.7%	33.0%	43.7%

words, younger riders showed a higher probability of having no injuries and a lower probability of fatalities. Conversely, older riders showed a lower probability of no injuries and a higher probability of fatalities. The change in the injury severity for older riders is more pronounced compared to younger riders (from 10.9% increase in no injury to 11.8% decrease in fatality for younger riders vs. from 35.6% decrease in no injury to 38.8% increase in fatality for older riders). This difference can mainly be related to the physiological differences between older riders and younger riders, as older riders are more vulnerable to severe injuries. Furthermore, older people generally show a longer response time to events while driving, which in turn affects their critical driving behaviours (e.g. steering and braking) (Dozza, 2013) and increases their chance of getting involved in a more severe crash. Other similar studies by Savolainen and Mannering (2007) and Quddus, Noland, and Chin (2002) also show the same trends.

Motorcycle rider condition, as one of the variables violating parallel line assumption, is found to have the most pronounced effect on the injury severity outcome. Having the

Table 5. Comparison between PO, NPO, PPO, and MNL models using AIC and BIC.

Model	AIC	BIC
PPO	15,953.13	16,217.81
NPO	15,984.31	16,472.94
PO	16,091.33	16,233.84
MNL	15,975.30	16,463.92

normal condition as the base category, being under the influence of drugs and alcohol (intoxicated driving) reduces the no injury probability by 64.4%, while increasing the probability of fatality by 124.3%. A recent study by Liu, Liang, Rau, Hsu, and Hsieh (2015) indicates that intoxicated motorcycle riders present various characteristics and body injury patterns compared to sober drivers. Operator condition (i.e. being under the influence) has previously been found to be a major contributing factor to other crash types as well (Pour-Rouholamin, Zhou, Zhang, & Turochy, 2016).

The next variable under motorcyclist characteristics is whether the rider wears a helmet. The specific result and obtained average direct pseudo-elasticities demonstrate that not wearing a helmet significantly affects the injury severity outcome, resulting in an 18.2% decrease in no injury and a 19.9% increase in the fatality probability. Abbas, Hefny, and Abu-Zidan (2012) disclosed that on a global scale helmet non-usage percentage is the most significant factor affecting motorcyclists' fatality rate. Furthermore, analyses (Rice et al., 2016) have shown that motorcycle helmet usage is associated with a considerable decrease in the risk of head injury and fatal injury, and with a moderately decreasing risk of neck injury. However, the effect of not wearing a helmet on the probability of severe injuries in the studied dataset is not as strong as would be expected. It is also believed that the type of helmet used can significantly affect the type and severity of the injury (Brewer et al., 2013; Erhardt, Rice, Troszak, & Zhu, 2016).

4.3. Temporal variables

Time of the year, indicated by season, is found to be significantly associated with injury severity. Crashes during the summer are more likely to be fatality (22.9%), while crashes occurring in winter are less likely to be fatality (21.3%). A possible explanation for this finding would be the motorcycle traffic volume variations, peaking during the summer months when the weather allows for riding. Given this, adverse weather conditions are shown to have fewer fatalities and severe crashes compared to clear weather (Eisenberg & Warner, 2005). Generally, drivers adopt various kinds of risk-compensating behaviours, including speed reduction during adverse weather conditions, which subsequently reduces the severity of crashes (Kilpeläinen & Summala, 2007). Gill and Goldacre (2009) also indicated that hospital admissions for motorcyclists in August are 33% above the annual average and in January 43% below the annual average.

Regarding the day of the week, motorcycle crashes that happened during the weekend are found to have a higher probability of fatality (12.2%) to riders. Blackman and Haworth (2013) and Zambon and Hasselberg (2006) also found a similar trend. An interesting finding by Peek-Asa, McArthur, and Kraus (1999) shows that weekend motorcycle riders are more likely to wear non-standard helmets compared to weekday riders. Given the significance of helmet use in this study, this finding may further corroborate the role of helmet use in severe injuries.

4.4. Crash variables

The type of setting, urban vs. rural, is found to be significantly associated with injury severity and one of the factors that violates the parallel line assumption. The calculated elasticities indicate that crashes that happen in rural areas compared to urban areas show various behaviours. Specifically, crashes in rural areas show an increase in no injury (22.1%), an increase in incapacitating injury (61.2) and a decrease in fatality (6.3%). However, rural areas have traditionally seen more fatal crashes than urban areas. Specifically related to this paper, single-vehicle crashes in rural areas are known for their higher likelihood of fatality compared to crashes in urban areas (Adinegoro, Haworth, & Debnath, 2015). It should be noted that emergency medical services are more accessible and faster in urban areas, which may reduce the severity of crash-related injuries (Pour-Rouholamin & Zhou, 2016a).

Adverse weather conditions and wet surfaces were both found to decrease the severity of injuries sustained by motorcycle riders. More specifically, adverse weather conditions are associated with a 28.1% reduction in the likelihood of fatalities and a 25.8% increase in the likelihood of no injuries. For wet surface conditions, these numbers change to 29.6% and 27.2%. These findings are reasonable, as during adverse weather conditions, when sufficient sight distance is not provided or on wet surfaces, road users tend to show more risk-compensating behaviours, pay more attention to their surroundings, including roadway and other vehicles, maintain longer headways, and drive at lower speeds (Shaheed & Gkritza, 2014). Haque et al. (2012) also demonstrated that riding on wet pavement often results in less severe injuries. Furthermore, it is possible that fewer casual riders (e.g. riders more willing to ride with little or no protective equipment, less training, and/or less experience) would expose themselves to such adverse conditions. This may suggest that the population of riders that crash in these conditions are not the same ones that are crashing during dry conditions in some cases. Given that North Carolina is ranked ninth in the United States regarding average total yearly precipitation, this finding is considerable, requiring more attention to the issue.

Riding during the night in darkness, whether any kind of lighting is provided or not, also significantly affects the severity of motorcycle rider crashes. It should be noted that darkness, when there is no lighting provided, increases the severity of injuries (13.9% increase in probability of fatality). Several factors might explain this finding. For instance, Bella, Calvi, and D'Amico (2014) have found the dominance of sleepiness, glare, dark adaption, reduced visibility of roadways, signs and markings, and a higher proportion of drunk drivers as contributing factors to more severe injuries at night. To delineate between lit and unlit roadways, Zhang, Yau, Zhang, and Li (2016) also disclosed that driving at night without lighting is more likely to cause fatigue-related crashes, with following severe injury outcomes.

The estimation results presented in Table 3 identified a significant relationship between the type of accident and crash injury outcome. Violating the parallel line assumption, a collision with a fixed object is found to considerably increase the probability of severe injuries. This parameter is the second strongest parameter, increasing the probability of fatalities by 92.7%. It is believed that the injury outcome for motorcycle riders hitting roadside objects (e.g. utility poles, curbs) tends to be more severe. Overturn/rollover is also another confounding factor that violates the parallel line assumption. The specific findings of this study indicate a 48.9% reduction in the probability of no injuries, a 5.0% decrease in the probability of fatalities, and a 10.4% increase in the probability of non-incapacitating (B-) injuries. Daniello and Gabler (2011) calculated the fatality risk of colliding with a fixed object to be 15 times greater than the fatality risk of an overturn collision.

Reckless riding refers to the deliberate violation of safe riding practices (Taubman-Ben-Ari, Mikulincer, & Gillath, 2004), such as following too close, disregarding traffic control devices, failure to yield the right-of-way, or multiple lane changing. Reckless riding is associated with more severe injuries and potentially increases the probability of fatality by 30.2%. Speeding is another parameter violating the parallel line assumption and necessitating the development of a PPO model. Given this, speeding shows a non-linear change in the severity outcome of injuries, so that it increases the likelihood of fatalities by 68.7% and decreases the likelihood of no injuries by 12.8%. The relationship between speeding and injury severity can be explained as higher speeds leading to a higher probability of overturn/rollover and higher impact speeds with fixed objects, increasing the likelihood of more severe injuries.

Roadway curvature was the last significant parameter violating the parallel line assumption. Having the straight highways as the reference category, motorcycle crashes that happen at curves are more likely to produce fatalities (43.7%) and less likely to result in no injuries (3.1%). To better understand the effect of curvature, Schneider et al. (2010) explored the effect of horizontal curvature on single-vehicle motorcycle crashes on rural two-lane highways. Their analysis revealed a significant increase in the frequency of motorcycle crashes, given that the rider negotiates a short radius and insufficient length of the curve. The higher the frequency of the crashes, the higher the risk of injuries to vulnerable motorcycle riders. Roadway curvatures are known for reducing available sight distance and decreasing vehicle-controlling capabilities and subsequently increasing the probability of crashes and fatalities.

4.5. Comparison to other studies

Table 6 compares our findings with those of previous studies focusing on single- and multi-vehicle motorcycle crashes. This comparison highlights the similarities and differences between our study and others with respect to significant confounding factors, showing one of the unique aspects of this study. When looking at this table, a few points are worth mentioning. For example, all the reviewed studies explored that factors such as older riders, driving under the influence (DUI) riding, not wearing helmets, crashes during weekends, darkness, crashes with fixed objects, reckless riding, and speeding were associated with higher injury severities. In contrast, factors such as crashes during winter, adverse weather condition, wet surface, and dark lighting conditions decrease the severity of crashes. Additionally, crashes in rural areas and crashes occurred along the curves showed fluctuating effects of injury severity, supporting the results of previous studies to some extent. Conflicting findings were obtained for the effects of motorcyclists' age and season on injury severities. More specifically, whereas our study findings indicate that the younger riders (less than 24) were associated with lower crash severities, Pai and Saleh (2007) demonstrated that the crash injury severities increase among younger riders. Moreover, unlike our study, Shaheed, Gkritza, Zhang, and Hans (2013) explored that the summer resulted in crashes with lesser injury outcomes. While the underlying cause of these inconsistent results cannot be described with any reasonable certainty, the possible reasons to obtain such results include using different crash severity levels (for instance, Shaheed et al. (2013) combined A-injury and fatality which potentially affects the magnitude and direction of the results), various geography

Table 6. Comparison of the results with other studies.

Explanatory variable	Our study	Related study: Single-vehicle motorcycle crash: Lin, Chang, Huang, Hwang, and Pai (2003)	Savolainen and Mannering (2007)	Schneider and Savolainen (2011)	Shaheed and Gkritza (2014)	Multi-vehicle motorcycle crash: Shaheed et al. (2013)	Chung, Song and Yoon (2014)	Rifaat, Tay and de Barros (2012)	de Lapparent (2006)	Pai and Saleh (2007)	Quddus et al. (2002)	Chang et al. (2016)	Cunto and Ferreira (2016)
Motorcyclist characteristics													
Age													
Younger rider (less than 24)	↓[a]	–[c]	–	–	–	–	–	–	–	↑	–	–	–
Older rider (65 and over)	↑[b]	–	↑	↑	–	–	–	–	↑	↑	–	↑	–
DUI driving?													
Yes	↑	–	↑	↑	↑	–	↑	↑	–	–	–	–	–
Helmet used?													
No	↑	–	↑	↑	↑	↑	–	–	–	–	–	↑	↑
Temporal variables													
Season													
Summer	↑	–	–	–	–	↓	–	–	–	–	–	–	–
Winter	↓		–	–	–	–	–	↓	–	↓	–	–	–
Day of week													
Weekend	↑	–	–	–	–	–	–	–	–	–	–	–	↑
Crash variables													
Type of setting													
Rural	↑↓	↑	–	–	↑	–	–	–	–	–	–	–	–
Weather condition													
Adverse	↓	–	–	–	–	–	–	–	–	↓	–	–	–
Surface condition													
Wet	↓	–	↓	–	↓	–	–	–	–	–	–	–	–
Lighting condition													
Dark – lit	↓	↓	↓	–	–	↓	↓	↓	↓	↓	–	↓	–
Dark – not lit	↑	↑	↑	↓	–	↑	↑	↑	↑	↑	–	↑	↑
Accident type													

(*Continued*)

Table 6. Continued.

		Related study											
		Single-vehicle motorcycle crash				Multi-vehicle motorcycle crash							
Explanatory variable	Our study	Lin, Chang, Huang, Hwang, and Pai (2003)	Savolainen and Mannering (2007)	Schneider and Savolainen (2011)	Shaheed and Gkritza (2014)	Shaheed et al. (2013)	Chung, Song and Yoon (2014)	Rifaat, Tay and de Barros (2012)	de Lapparent (2006)	Pai and Saleh (2007)	Quddus et al. (2002)	Chang et al. (2016)	Cunto and Ferreira (2016)
Fixed-object	↑	↑	↑	↑	↑	–	–	–	–		↑	–	–
Overturn/rollover	↑↓	–	–	–	↑	–	–	↑	–	–	–	–	–
Contributing factor													
Reckless	↑	–	↑	–	–	–	–	↑	–	–	↑	–	–
Speeding	↑	↑	↑	↑	↑	–	↑	↑	–	↑	–	–	↑
Roadway characteristics													
Curve	↑↓	–	↑	–	–	–	–	↑	–	–	–	↑	–

↓[a] Increasing effect on injury severity.
↑[b] Decreasing effect on injury severity.
–[c] Not studied/non-significant.

of study locations (the United States, Canada, Taiwan, and the United Kingdom) representing various riding behaviours and highway design standards, different types of the helmet in the market, and various state and community motorcycle safety programmes. To be specific, North Carolina Motorcycle Safety Education Programme offers several basic courses for motorcycle riders with a minimum of 6 months riding experiences, resulting in a possible decrease in the injury severity of crashes. It is worth mentioning that in most reviewed studies, the effects of contributing factors on injury serveries of single- and multiple-vehicle motorcycle crashes show the same trends. Crashes in rural areas, overturn/rollover crashes, and crashes while negotiating a curve showed fluctuating effects on injury severity based on our study while these factors have all showed an increase in the probability of higher injury severities in other studies, whether single-vehicle or multi-vehicle.

5. Conclusions and recommendations

This paper investigated risk factors that affect the injury severity of the riders in single-vehicle, single-rider motorcycle crashes in North Carolina. Several reasons led the researcher to put their emphasis on this group of riders, mainly to make a homogenous crash dataset to the extent possible that offsets the effect of other possible factors and control the results for actual confounding variables. Given the ordered nature of crash severity, ranging from no injury to fatality, and as discussed in the model comparison section, ordered-response models were found to be more appropriate (Pour-Rouholamin & Zhou, 2016b). Three ordered-response models, PPO, NPO, and PO, as well as one unordered model, MNL, were nominated for modelling purposes. Several factors at the motorcycle rider, temporal, and crash level were found to significantly affect the injury outcome of the riders, among which the variables of DUI riding, rural setting, hitting a fixed object, overturn/rollover, speeding, and driving on a curved roadway were found to violate the parallel line assumption, requiring the development of a PPO model. A comparison between all these modelling techniques using AIC and BIC showed that the PPO model outperforms the other three models and produces better results. Furthermore, a comparison between the results of our study and those of others (single-vehicle and multi-vehicle motorcycle crashes) has been made that highlights the differences and stresses the novelty of findings.

The analysis of the data identified various issues that can be addressed to reduce the injury severity of single-vehicle, single-rider motorcycle crashes. These could potentially include safety awareness campaigns, educational efforts, and law enforcement. Based on the obtained average direct pseudo-elasticities, it is suggested that if financial constraints exist, priority should be given to the parameters with higher elasticities, as addressing these issues could potentially result in more effectively alleviating the severity of injuries. The findings require an evidence-based injury prevention initiative that targets older motorcycle riders, DUI riders, speeders, reckless riders, and non-helmet riders, given that these groups are found to have increased injury severity. North Carolina currently has several educational programmes to promote safety among motorcycle riders; however, these efforts should focus more on the factors above.

With an increase of 27.35% in the population of persons 65 years and over in North Carolina in the 2000s, addressing older riders is necessary through strategies like counselling by healthcare providers or self-assessment tools that can help older riders recognize if they can ride on their own. The DUI condition has the strongest effect on the probability of motorcycle rider injury severity. It should be noted that the role of alcohol is more noticeable in motorcycle-related crashes than in car crashes. The reason is that riding a motorcycle needs balance, operating two brakes, steering, and shifting while navigating through potential hazards such as rough pavement. These actions are considerably affected by the rider's condition, resulting in incidents and possible severe outcomes. DUI driving prevention campaigns for motorcycle riders, tied with stricter enforcement rules, are recommended for North Carolina. Currently, North Carolina has set the threshold of 0.08 BAC for non-commercial vehicle operators to be illegally impaired. However, if you have previously been convicted of DUI driving, this threshold drops to 0.04, representing a stricter rule.

Not wearing a helmet is found to increase the probability of severe injuries; however, the effect is not as strong as would be expected in terms of magnitude. Interestingly, a study by Barrette, Kirsch, Savolainen, Russo, and Gates (2014) revealed that after repealing a universal helmet law in lieu of the partial helmet law in Michigan, less severe injuries were observed at intersections, at low speeds, and in inclement weather conditions. However, the injuries were found to get more severe when speeding is involved, or when the rider was under the influence of alcohol and/or drugs. In other words, speeding and DUI driving can offset the benefit of wearing a helmet. This can justify the stronger effect of DUI motorcycle riding and speeding on the injury severity of riders, compared to not wearing a helmet.

Lighting condition has also been found as one of the significant factors. HSIS data provide crash locations based on the mileposts on the majority of roadways. Using this, hotspot locations with respect to frequency and severity of motorcycle crashes can be investigated on their lighting conditions. The findings of this study suggest that providing lighting at such locations can significantly decrease the probability of severe injuries. Crashes during the weekend and hitting a fixed object were among significant variables increasing injury severity. A possible explanation for the appearance of the weekend and fixed-object crashes in the final model with the same direction of effect on injury severity would be that motorcycle riding during weekends is generally more for recreational purposes than for commuting, which is associated with a greater likelihood of having severe single-vehicle, fixed-object crashes.

Regarding the considerable effect of roadway curvature on the probability of severe injuries, the use of advanced curvature warning signs as well as chevrons through the horizontal curves is suggested. A field observation of the hotspot locations might be necessary, as some of these locations may already have the appropriate signs but lack adequate visibility. In addition to their visibility and legibility (Balali & Golparvar-Fard, 2016), signs are only effective when they clearly convey the intended message in both day and night-time conditions (Khalilikhah & Heaslip, 2016; Khalilikhah, Heaslip, & Song, 2015). High-friction surface treatment at problematic locations is another possible countermeasure for a state with such a high precipitation level.

Similar to most studies, this study also has some limitations. The most important limitation of this study comes from the inevitable role of human error in the data collection process by police officers that affects the level of detail and accuracy for the obtained significant variables. An appropriate measure of exposure to crash is also missing in the database. Currently, age is considered as a measure of exposure; however, using other measures such as the age of licensure or driving experience, if available, might potentially replace age and provide more reliable results.

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