Effects of Motorways on Road Safety in Ireland

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ABSTRACT: In Ireland, high-speed motorways were built around the year 2008 to 2010. In order to investigate the effect of motorways on road safety, the research paper aims at identifying the shift of contributing factors related to vehicular crashes, before-and-after the construction of motorways/expressways. Typically, several factors are involved for accidents on motorways, but a better understanding is needed to find the relationship between injury severity and its contributing factors. The current study seeks to find the contributing factors for before-and-after the construction of motorways. In this study, the before period is considered from 2003-2007, and 2012 to 2016 have been considered as the after period. Traditionally, injury severity (fatal, severe, moderate, no injury) is considered as an ordered (ordered logit/probit model) or non-ordered (Multinomial logit model) variable. For the proportional ordered logit model, variables should meet the parallel line assumption. However, multinomial logit model ignores the inherent hierarchical nature of accident severities. To overcome these drawbacks partial proportional model are developed, which helps in estimating the models that are less restrictive (ordered model) but more parsimonious and interpretable than (multinomial logit model). The results indicate that for before period, the contributing factors for fatal accidents were evening peak hour, accident with more than two vehicles, dry surface condition, frost, ice, snow and others surface condition, single-vehicle primary collisions, rear-end collisions and private cars. While for 2012-2016, the major contributing factors for fatal accidents were morning peak hour, evening peak hour, straight road character, single-vehicle collision type, rear-end collision type, not learner driver, young and mid-age grouped drivers.

KEYWORDS: Motorways, Injury Severity; Before-After Study; Partial Proportional Odds Model

1 INTRODUCTION

Motorways act as a backbone to the transportation infrastructure, which connects different parts of the city and country for transporting goods and essential services. In Ireland, these high-speed roadways were built around the year 2008 and 2010. Typically, with an increase in the kilometres of motorways, the number of accidents related to motorways could be increasing. Pre 2008 era was considered as the boom in the Irish economy, which resulted in the usage of private vehicles to a greater extent [1]. However, with upgradation of dual carriageways to motorways, the effect of motorways on safety needs to be investigated for future reference.

Crash severity is typically divided into three categories i.e., fatal, serious, and minor, but fatal and serious severity has always been a significant indicator of measurement for the government as it implicates the social influence and results in a higher amount of financial loss [2]. The principal aim of the transport agencies is also to reduce the number of crash count as well as its severity using safety programs, selection of suitable countermeasures, development of new policies and enforcing the policies. The crash frequency modelling majorly helps in the understanding of likely numbers of crashes and document the unsafe zones[3].

The crash severity model focuses on the likelihood of odds of a crash being fatal, serious or minor. The ordered logit/probit model, multinomial logit model, generalised ordered logit model, mixed logit model are some of the models that are used for estimating injury severity [4-7]. These models mainly have some methodological concerns like unobserved heterogeneity, missing variables, crash underreporting, etc. Latent class clustering model is one of the models which helps in understanding the unobserved heterogeneity of the data. The dataset is mainly divided into latent classes by unobserved or latent categories. The latent classes are mainly optimised by statistical criteria, and those different types of variable criteria are analysed without any standardisation, which helps in eliminating the bias[8]. To account the stationary factors and dynamic factors of explanatory parameters simultaneously, for the possibility of systematic variations of the parameter effects of unobserved heterogeneity, a dynamic binary random parameters (mixed) logit model is employed by having an additional error term which does not follow the normal distribution [3, 9].

The crash severity models focus on the likelihood of occurrence of a crash which is fatal, serious or minor. The ordered logit regression model is a type of probability model which helps in finding out the probability of the severity of the accident, where the model list down the category based upon its significance and these severity level are related to each other and are ranked according to their hierarchy. These characteristics of the model are beneficial for estimating the probabilities[4, 10, 11]. One of the major issues for the ordered logit model is that predictor variables should meet the parallel line assumption, which is often violated and could mislead the results[12].

Another majorly used conventional model is Multinomial Logit Model (MNL), when the data is not well ordered. It is a type of discrete model where the likelihood of a dependent variable has been estimated using multiple independent data, one of the significant drawbacks noted for MNL is that it could suffer from correlations from outcomes [3]. Thus to overcome the drawbacks of ordered and multinomial models, partial proportional odds model has been used where "it helps in estimating models that are less restrictive than ordered logit (whose assumptions are often violated) but more parsimonious and interpretable than those estimated by a non-ordinal method such as multinomial logit model" [12].

The major contributing factors for road accidents are mainly environmental, road characteristics, and driver characteristics [13-15]. In Greece, a research study explained that using the traffic loop detector data, 5 minutes before and an hour after the occurrence of the accident, has helped in understanding the behaviour of severity of accidents. It was found that truck size, flow, accident type, and engine size have significant impacts on the severity of the accident. The collision of a vehicle with an object and low engine size vehicles has the highest probability of having severe injury[8].

Road characteristics are also one of the major contributing factors for the crashes on motorways [13]. Highway having a rolling terrain increases the odds of an accident, which is mainly because of lower sight distance. The presence of ice reduces the probability of accidents. An increase in the vertical grade by 5%, increases the probability of having accidents. Further, lane width and average daily traffic play a vital role in the severity of accidents. [13, 16].

Environmental conditions like rain, light conditions have critical impacts on the severity of the accidents [10, 17, 18]. Lower temperature, fewer thunderstorm days, and the number of fog occurrences increase the chance of crashes. However, factors like rain and wind have a negative association [19].

Overall, many studies have performed accident severity analysis using different models. The past studies had mainly used Ordered Logit Model or Multinomial Logit Model. There are very few studies that explain the Partial Proportional Model (PPO). The present study focused on understanding the effect of motorways on crashes by developing two PPO models (before and after the construction/upgradations to motorways). Also, to nullify the effect of construction activities, two separate time intervals were selected for the before-and-after study. Data between 2003 to 2007 was considered as before period and data between 2012 to 2016 was considered as after period. The results from the developed models would help the Road Safety Authority (RSA) to find out the major contributing factors on high-speed road crashes, and the results could be used to propose guidelines to improve safety on motorways.

2 METHODOLOGY AND DATA

This section describes data collection, data processing, and focuses on the methodology adopted in this research paper.

2.1 Data Collection and recoding

The accident data for the years 2003 to 2007 and 2012 to 2016 has been collected from the Road Safety Authority (Ireland). The motorways in Ireland are predominantly two-lane dual carriageways and connect major inter-urban centers. From the crash database, the crashes during before period and after period were selected by using speed limit and road classification variables. Crashes on roads with the speed limit of 100 kmph and 120 kmph of motorways and dual carriageway were considered for analysis. During the year 2003 and 2004, the speed limit of motorways and dual carriageway were lower and hence, the speed limit of 60 kmph and 70 kmph were considered for these two years. A total of 564 and 1074 crashes were observed during before and after periods, respectively. Few of the samples have missing variables and hence, omitted from the data considered for model development. These samples were less than 7% of the total crashes that occurred during before and after periods. Finally, the total number of 527 and 1061 crashes were used for model development for before and after periods, respectively.

Table 1 explains the descriptive statistics of all the dependent and independent variables. The categories in each variable are different, and few of the categories have been merged, which were smaller in number to reduce the bias and degree of freedom. The merging of the categories was dependent on the type of the variable.

The 'time of day' variable explains the occurrence of crashes on a particular time range; rather than having 24 different categories, the time was divided into four categories. Morning peak period was considered from 07:00 to 09:59, the afternoon off-peak period was considered from 10:00 to 15:59, evening peak hour was considered as 16:00 to 18:59, and night hours were considered to 19:00 to 06:59 [20]. In the category 'Weekday' instead of having seven different categories, variables were divided into two categories' weekday' (Monday to Friday) and 'weekend' (Saturday and Sunday). In the case of the number of vehicles involved in the crash, it was categorised as a single-vehicle involved, two vehicles involved, and more than two vehicles involved. The light condition was drawn down to three categories: 'day-good visibility' and 'day-poor visibility' were merged in 'day condition' category while categories like 'dark-good lighting,' 'dark-poor lighting,' 'dark-unlit lighting' and 'dark-no lighting' were merged into 'dark condition' category while the third category was unknown. The weather condition variable was rearranged in three categories, which were dry, wet, and others.

Table 1: Descriptive Statistics

Variable	Category	2003-2007		2012-2016	
		Frequency	Percentage	Frequency	Percentage
Accident Type	Fatal	45	8.5	47	4.4
	Serious	47	8.9	82	7.7
	Minor	435	82.5	932	87.8
Time of Day	Morning peak	91	17.3	175	16.5
	Afternoon off-peak	159	30.2	385	36.3
	Evening peak	103	19.5	231	21.8
	Night off-peak	174	33.0	270	25.4
Day of Week	Weekend	156	29.6	242	22.8
	Weekday	371	70.4	819	77.2
# Vehicles Involved	Single Vehicle Involved	184	34.9	446	42.03
	Two Vehicle Involved	253	48.0	460	43.35

	> 2 Vehicles Involved	90	17.1	155	14.62
Light Condition	Day Time	347	65.8	691	65.1
	Dark Time	174	33.0	355	33.5
	Unknown	6	1.1	15	1.4
Weather Condition	Dry	396	75.1	736	69.4
	Wet	90	17.1	256	24.1
	Others (Snow, Fog, High Winds, etc.)	41	7.8	69	6.5
Surface Condition	Dry	350	66.4	621	58.5
	Wet	152	28.8	376	35.4
	Others (Frost, Ice, Snow, etc.)	25	4.7	64	6.0
Road Character	Straight	390	74.0	927	87.4
	Bend	47	8.9	79	7.4
	Others (Hillcrest, Gradient, etc.)	90	17.1	55	5.2
Primary Collision Type	Single Vehicle	137	26.0	420	39.6
	Rear End	178	33.8	374	35.2
	Others (Head On, Angle, etc.)	212	40.2	267	25.2
Driver Learner	Not Learner	309	58.6	738	69.6
	Learner	43	8.2	51	4.8
	Unknown	175	33.2	272	25.6
Class of Vehicle					
	Private Car	402	76.3	858	80.9
	HGV's	38	7.2	40	3.8
	Others (Taxi, Van, Hackney Car, etc.)	87	16.5	163	15.4
Age					
	<=30, Young Age Group	223	42.3	344	32.4
	31-45, Mid-Age Group	185	35.1	420	39.6
	46+, Old Age Group	119	22.6	297	28.0
Sex	Male	333	63.2	646	60.9
	Female	194	36.8	415	39.1

In the 'road characteristics' variable, the primary categories are 'straight' and 'bend' while the rest of the categories like 'hillcrest,' 'gradient,' 'others', and 'unknown' which were having a significantly lesser number of samples and hence, merged. In the 'primary collision type' variable, the initial categories were 'single-vehicle collision' and 'rear-end collision' while other variables like 'head-on collision', 'angled collision', and 'others' were merged into a single category. Also, due to the presence of separate lanes for each direction, the possibility of a head-on collision is less. The 'driver learner' variable has been categorised in four categories where 'learner accompanied,' and 'learner unaccompanied' categories were merged in the 'learner' category while the rest of the two categories were 'Not learner' and 'unknown'. In the 'Class of vehicle' variable, 'private car' and 'HGV's' were considered as separate categories, while categories like 'taxi', 'van', 'hackney car', 'other' were merged into the third category. Rather than keeping 'Age' variable continuous it was categorised as three categories, the age group of 16 to 30 were represented as a young age group, persons between 31 to 45 were represented as 'mid-age group' and persons having age more than 45 was considered as 'old age' category.

2.2 *Partial Proportional Odds*

The study explains the severity of the accidents on the motorways, i.e., Fatal (type=1), Serious (type2), and Minor (type 3). These three categories form up to become the dependent variable, *Y*. The probability that *Y* is a particular j outcome category can be expressed as follows

$$P(Y_i > j) = P_{ij} = \frac{e^{(\alpha_j + X_i \beta_j)}}{1+e^{(\alpha_j + X_i \beta_j)}} \tag{1}$$

Where, Pij represents the probability of a crash 'i' experiencing injury severity level j, and X is the matrix of predictor variables. j = 1, 2,….,j-1; β is the regression coefficient to be estimated, and αj is the intercept for jth logit.
'βj' has different values for each level and category of the dependent variable when a dependent variable does not meet the odd proportional test.
'βj' has only one value for all the levels and categories when the dependent variable is similar for the parallel line assumption test.

The PPO model used for the study was developed using gologit2 package in Stata [12]. The developed models are discussed below.

3 RESULTS AND DISCUSSION

The results of assuming the likelihood of crash severity were performed using the Partial Proportional Odds model, and results were generated using the gologit2 package in Stata software. The severity level was categorised in three categories i.e. fatal (1), serious (2), and minor (3). The results for gologit2 can be interpreted in the same manner as the results of binary logistic regression. So, the results could be interpreted in a similar manner by grouping three categories in binary form. The first panel (Panel 1) of estimated in Table 2 and Table 3 explains that 'fatal injury' contrasts the severity outcome to the other two severity categories ("Serious" and "Minor") and the second panel (Panel 2) estimates in Table 2, and 3 explains that "Fatal and Serious" injury contrast the severity outcome to 'minor injury'.

Table 2 Partial Proportional Odds Model for Crash Severity (2003-2007)

Variables		Panel 1		Panel 2	
		Coefficient	p-value	Coefficient	p-value
Time of Day	Morning Peak Period	-0.104	0.812	-0.104	0.812
	Afternoon off-peak Period	0.313	0.451	0.313	0.451
	Evening Peak Period	2.695	0.000	0.214	0.624
	Night off-peak Period	NA	NA	NA	NA
Weekday	Weekend	NA	NA	NA	NA
	Weekday	-1.183	0.011	0.255	0.378
# Vehicles Involved	Single	-1.788	0.001	-0.647	0.110
	Two	NA	NA	NA	NA
	>2	1.517	0.021	0.050	0.896
Surface condition	Dry	3.307	0.000	-0.679	0.156
	Wet	NA	NA	NA	NA
	Others (Frost, Ice, Snow, etc.)	4.046	0.001	-0.395	0.620
Road Character	Straight	-2.147	0.003	0.522	0.218
	Bend	NA	NA	NA	NA
	Others (Hillcrest, Gradient, etc.)	-1.870	0.043	0.756	0.142
Primary Collision	Single Vehicle	1.294	0.002	1.294	0.002
	Rear End	0.8101	0.021	0.810	0.021
	Others(Head on, Angle, etc.)	NA	NA	NA	NA
Class of Vehicle	Private Car	0.6983	0.035	0.698	0.035
	HGV's	0.717	0.251	0.717	0.251
	Others(Taxi, Van, Hackney Car, etc.)	NA	NA	NA	NA
Age	Young-Age Group (16-30)	-0.629	0.229	0.438	0.211
	Mid-Age Group (31-45)	-1.416	0.022	0.731	0.043
	Old Age Group (46+)	NA	NA	NA	NA
Sex	Male	-3.126	0.000	-0.785	0.013
	Female	NA	NA	NA	NA

Note: NA indicates the reference category.

In Table 2, variable with a p-value less than 0.05 was considered as the significant variable at a 95% confidence interval. If any of the significant variables have a positive coefficient, then it tends to increase the odds of sustaining the fatal or serious injury, while the negative coefficient value suggests that the odds of getting involved in a fatal or serious injury would reduce.

For the year 2003-2007, predictor variables such as 'evening peak period,' 'weekday,' 'single vehicle involved,' crashes with more than two vehicles,' 'dry surface condition,' 'ice, snow, and other surface conditions,' 'straight road,' 'hillcrest, gradient, and other roads,' 'young age group,' 'mid-age group' and 'male' were the categories which violate the parallel line assumption (p-value < 0.05), while other remaining categories accepted the parallel line assumption (p>0.5).

From the first panel (Panel 1: Fatal v/s Serious + Minor), the odds of a fatal crash during the evening peak period is 14.73 times when compared to off-peak night period.

The odds of fatal accident on weekday is 0.83 times when compared to weekend. The major reason could be the higher traffic volume which reduces average speed and lowers the risk of fatal accident.

The involvement of single vehicular fatal accidents has odds of 0.16 times of occurrence. Typically, single vehicle crash is result of run-off or hitting a stationary object such as barriers, which could tend to be a minor or serious injury crash. However, the odds of fatal accident involving with more than two vehicles is 4.52 times when compared to crashes with two vehicles, which could be a result of sudden drop in speed on high-speed roads.

The dry surface condition shows the odds of 27.11 times the occurrence of fatal accident when compared to wet surface condition. Likewise, the odds of getting involved in a fatal accident on frost, ice, snow and other surfaces is 56.82 times when compared to wet surface condition, which is highest among the three categories.

The straight road characteristics have odds of 0.11 times of occurrence of fatal accidents, while odds on hillcrest, gradient and other types of road characteristics have 0.15 times of occurrence of a fatal crash compared to roads with a bend. Drivers tend to drive carefully in challenging conditions and having a higher amount of traffic on the straight road would reduce the risk of involvement in a fatal accident. The odds of occurrence of single-vehicle fatal accident is 3.62 times when compared to the other collision types. Likewise, the odds of getting involved in rear-end type fatal accident is 2.24 times when compared to the other collision types. A higher amount of single-vehicle accidents could be due to the road characteristics and misjudgment of road alignment, while for rear-end collision, the total number of vehicles involved in the accident is higher, resulting in higher chances of fatality. The odds of getting involved in a fatal accident by private car is 1.99 times higher than other vehicular categories because the private car drivers have higher odds of driving a car at high speed which makes it challenging to handle. However, the odds of fatal accident for mid-age group is 0.31 times the old aged group drivers. This explains that a mature driver drives carefully, resulting in lower chances of fatal accidents. The odds of occurrence of fatal accident for male drivers is 0.04 times female drivers.

Table 3 Partial Proportional Odds Model for Crash Severity (2012-2016)

Variables		Panel 1		Panel 2	
		Coefficient	p-value	Coefficient	p-value
Time of Day	Morning Peak Period	1.347	0.004	1.347	0.004
	Afternoon Period	0.622	0.087	0.622	0.087
	Evening Peak Period	0.6369	0.055	0.636	0.055
	Night Period	NA	NA	NA	NA
# Vehicles Involved	Single	-1.131	0.002	-1.131	0.002
	Two	NA	NA	NA	NA
	>2 Vehicles	-0.473	0.132	-0.473	0.132
Road Character	Straight	0.709	0.028	0.709	0.028
	Bend	NA	NA	NA	NA
	Others(Hillcrest, Gradient, etc.)	0.449	0.416	0.449	0.416
Primary Collision	Single Vehicle	1.719	0.000	1.719	0.000
	Rear End	0.819	0.003	0.819	0.003
	Others(Head on, Angle, etc.)	NA	NA	NA	NA
Driver Learner	Not Learner	0.868	0.000	0.868	0.000
	Learner	0.971	0.087	0.971	0.087
	Unknown	NA	NA	NA	NA
Age	Young Age Group (16-30)	0.486	0.061	0.486	0.061
	Mid-Age Group (31-45)	0.617	0.012	0.617	0.012
	Old-Age Group (46+)	NA	NA	NA	NA

Note: NA indicates the reference category.

For the second panel (Fatal + Serious v/s Minor), the primary collision of single vehicles has higher odds of 1.02 times of occurrence of fatal and severe injury crashes, while the occurrence of a rear-end crash is 2.24 times when compared to other collision type. For the class of vehicle, the private car owner has odds of getting involved in fatal and serious crashes is 1.99 times when compared to other vehicle types. While for the mid-age group, the odds of getting involved in fatal and severe crashes are higher at 2.07 times of old age group and the male driver has the odds of getting involved in fatal and serious crashes to be 0.45 times than female drivers.

The result for the data of 2012-2016 are presented in Table 3. Variables with a p-value less than 0.05 were considered as significant at a 95% confidence interval. All the variables in this data have accepted the parallel line assumption (p>0.5).

For the first panel (Panel 1: fatal v/s serious + minor), the odds of getting involved in a fatal accident at the morning peak period is 3.8 times and that of having in the evening peak period is 1.87 times of off-peak night period. The odds of getting involved in a single vehicle fatal crash is 0.32 times, while the odds of having a fatal crash on a straight road is 2.01 times with respect to the reference category. The odds of involvement of single-vehicle collision in a fatal accident is 5.52 times, while the odds of having a rear-end crash is 2.24 times when compared to the reference category. For a driver who is not a learner the odds of having a fatal crash id 2.36 times; the odds of having a fatal accident for a young age group of people is 1.61 times, while for the mid-age group, the odds are 1.84 times when compared to the reference categories. The odds of occurrence of fatal v/s serious + minor and odds of having fatal + serious v/s minor are noted similarly.

The occurrence of having a severe or fatal accident during the morning peak period is very high, mainly because people would be in a hurry to reach their offices during the morning peak period. The odds of having a single vehicle involved in the accident are lower because, with the increase in the length of motorways, the daily traffic also increases, which results in lower average speed. However, driving on straight road results in higher chances of fatal or serious crashes as the driver tends to drive recklessly. The primary collision type of single-vehicle has a higher probability of fatal or severe crash comparing to rear-end crash because the road characteristics play a major role in it because of the higher speed of the vehicle crashes into other motorway components. The majority of the driver has the driving license, resulted in higher odds for a fatal or serious crash. The young age group and mid-age group both have higher odds of getting involved in a fatal or serious accident mainly because both of the age categories contribute the highest number of drivers on the road.

4 CONCLUSION

In Ireland, the motorway infrastructure was majorly built in the year 2008 to 2010. Two data sets have been considered to compare the before-after comparison of factors resulting in motorway and dual carriageway crashes, 2003-2007 is considered as before period, and 2012-2016 is considered as after period. The analysis has been performed for the speed limit of 100 and 120 kmph [21]. So the crashes considered would be on the significant part of the motorway and not near the junctions of motorways.

The accident severity dataset is available in the categorical form. The best way to obtain the likelihood of these categories is by using OLM, but the major drawback for OLM is the parallel line assumption. Partial Proportional Odds Model is one such model that can ease constraints in parallel line assumptions. The advantage of using this model is that "it helps in estimating models that are less restrictive than ordered logit (whose assumptions are often violated) but more parsimonious and interpretable than those estimated by a non-ordinal method such as multinomial logit model" [12].

For the year 2003-2007, predictor variables such as 'evening peak hour', accident with more than two vehicles, 'dry' surface condition, 'frost, ice, snow, and others' surface condition, 'single vehicle' collision type, 'rear end' collision type and 'private car' class of vehicle showed higher odds of having a fatal accident. However, predictor variables like 'weekday', 'single' vehicle collisions, 'straight road,' 'hillcrest, gradient, and other' road characteristics, 'mid-age group' and 'male' were observed to be significant but have lower odds of getting involved in a fatal accident. While for the variables which showed higher odds for fatal or severe crashes are 'single vehicle' collision type, 'rear end' collision type, 'private car' type of vehicle and 'mid-age group' showed the higher odds while 'male' showed significant values but had lower odds of having a fatal or serious accident.

For the year 2012-2016, the variables such as 'morning peak hour', 'evening peak hour', 'straight' road characteristics, 'single vehicle' collision type, 'rear end' collision type, 'not learner' driver, 'young age group' and 'mid-age group' showed significantly higher odds of getting involved in a fatal accident while 'single vehicle' involves in an accident showed significant values but had lower odds of getting involved in a fatal accident. The same variables were observed to be significant for severe and fatal crashes.

Accidents on the high-speed motorways were considered in this research study. However, the study does not consider the accidents on junctions and low-speed areas connecting the motorways, which could further merit the investigation.

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