A Logistic Regression Model for Hit and Run Bicycle Crashes in Victoria, Australia

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Abstract

Hit and run is an action that may lead to more sever crashes and may increase the number of fatalities on road network. So, hit and run action could be considered as a factor increasing the severity of road crashes. There are few studies explored the factors affecting hit and run crashes; however, there is no study investigated the effect of different crash attributes on hit and run crashes involving cyclists. This study explores the factors that increase the likelihood of hit and run in crashes that include at least one cyclist. The influence of roadway design specifications, vehicle features and road user characteristics on bicycle crashes is analysed. The data of bicycle crashes from 2004 to 2010 in Victoria, Australia, is used in this research. These factors are explored using chi-square tests and subsequently modelled using a Binary Logistic Regression model. The results of the analysis show that crash time, bicyclist's age and gender, helmet use (for bicyclist), other road user's intent, bicyclist's intent, traffic control (other road user's approach), traffic control (bicyclist's approach) and crash severity are significant variables in the Binary Logistic Regression model. Results of this study improve the understanding of crash parameters affecting bicycle hit and run crashes, therefore, some useful countermeasures can be designed to reduce the likelihood of this offensive action.

1. Research background

Bicycles are among vulnerable road users, so the bicyclists' safety on the road network has been the main concern of researchers and authorities (Poulos et al. 2015; Sanders, 2015). On average about 35 cyclists are killed and over 2500 cyclists are seriously injured in Australia each year (Australian Transport Safety Bureau, 2006). In 2008, in Australia, 27 fatalities were cyclists, down from 41 deaths the year prior (Australian Transport Safety Bureau, 2006). Therefore, it is necessary to understand the bicyclists' serious casualty problem in order to reduce the risk of fatality and serious injury crashes on the road network.

The hit and run act is a punishable offence and may result in increasing the severity of crashes as a result of the delay in receiving medical help by the victims. Roess et al. (2004) found that about 35% percent of deaths take place up to two hours after the crash. Therefore, identifying the factors that increase the likelihood of leaving the crash scene after the crash, may result in reducing the number of fatalities (Tay et al. 2008; kim et al. 2008).

Literature review of road safety research shows that few studies have been conducted to understand the main factors increasing the chance of hit and run occurrence. The impact of road features, environment and driver related factors, vehicle characteristics and crash characteristics on the likelihood of hit and run was mainly considered in different types of collisions (Solnick and Hemenway 1994; Solnick and Hemenway 1995; Kim et al. 2008; Tay et al. 2008, Tay et al. 2009; Tay et al. 2010; Macleod et al. 2012; Aidoo et al. 2013). Majority of these studies focused on pedestrian crashes and the role of pedestrian crash attributes in hit and run act (Solnick and Hemenway 1994; Solnick and Hemenway 1995; Kim et al. 2008; Macleod et al. 2012; Aidoo et al. 2013). Other studies considered all hit and run crashes in which at least one vehicle leaves the crash scene and studied the influence of crash variables on the hit and run action (Tay et al. 2008; 2009; 2010).

All these studies improved the understanding of crash parameters affecting the hit and run crashes, therefore, some useful countermeasures could be designed to reduce the likelihood of this offensive action. For instance, some of these studies found that increasing the level of enforcement such as presence of more police patrols or surveillance camera installations could be a good countermeasure to reduce the occurrence of the hit and run action (Tay et al. 2009; 2010).

The abovementioned studies considered the hit and run crashes either for pedestrian accidents or in general for other road users. They did not conduct separate investigation to understand the influence of different crash attributes on the hit and run act for the road crashes involving cyclists. Tay et al. (2008) found that the involvement of two wheel-vehicles in a crash results in higher perceived severity of the crash. Therefore, understanding the factors affecting this type of crashes could assist in identifying relevant countermeasures to reduce hit and run bicycle crashes. This could substantially improve bicycle safety on the road network.

In Summary, although studies carried out to explore the factors increasing the chance of hit and run action to take place in a collision, there is no enough focus on bicycle hit and run crashes. This study examines the effects of road and environment characteristics as well as human and vehicle specifications on hit and run crashes in which at least one cyclist is involved in Melbourne Metropolitan area in Victoria, Australia. This study identifies the factors that increase the chance of being involved in a hit and run crash, so some appropriate countermeasures can be defined to reduce this offensive action and decrease its consequences in Australia.

The next section of this paper outlines the database used in this study. Then, the data analysis method, which is utilized to understand the crash attributes affecting bicycle hit and run crashes, will be explained. The results from data analysis and model development are outlined next. This is followed by discussion of results and conclusion.

2. Data

Victorian crash data is utilized in this study. This database contains useful information on traffic crashes took place in Victoria, Australia. This database include crash attributes such as crash characteristics (e.g. crash time, crash severity etc.), road and environmental characteristics (e.g. road geometry, speed zone, control type, lighting condition etc.) and road user characteristics (e.g. age, gender helmet use, etc.). All two-vehicle crashes, including at least one bicycle, are extracted from the main database. On the other hand, a separate database containing hit and run information for Victoria traffic crashes is merged to the Victoria crash database. The database for hit and run contains all crashes for which at least one driver left the scene of crash on Victorian road network between 2004 and 2010.

Both databases are merged to explore how different crash attributes influence this offence to take place. The total number of crashes for these two years is 6962. Hit and run offence occurred for 11.7% of these crashes. The Victorian database contains all crashes in which one vehicle, two vehicles or multiple vehicles are involved. Two vehicle crashes occurred in Victoria are considered in this study. Table 1 outlines the variables and the classifications of each variable considered in this study.

3. Data Analysis Method

Previous section described the data that is used in this study. This section explains the statistical methods which are utilized to analyse the data. In the merged database, the dependent variable is “Hit and Run” which indicates whether the hit and run action took place. In this study, two-step analysis is carried out to explore the factors increasing the chance of leaving the crash scene.

In the first step, a Chi-Square test is performed to find out the independent variables (see Table 1) influencing the dependent variable (“hit and run” variable). The Chi-Square test is carried out using Pearson Chi-Square test (Levine et al. 2008). The dependent variable in this study is “hit and run” which is a binary variable. Therefore, the goodness of fit of discrete choice models with binary outcome such as Binary Logistic Regression and Binary Probit models are tested to find out the best modelling form describing the data. Binary Logistic Regression model is the most suitable technique. Therefore, in the second step, a Binary Logistic Regression model is developed in order to explore the relative importance of the significant variables. In the first step, Pearson Chi-Square test is conducted to identify the crash attributes which significantly affect the dependent variable. The chi-square statistic compared the tallies or counts of categorical responses between two (or more) independent groups. There are several types of chi-square tests depending on the way the data is collected and the hypothesis being tested (Levine et al. 2008). In this study, chi-square test is utilized to test the association of two categorical variables.

Table 1: Variables and the classification of variables considered in this study.

Variables	Dependent/ independent	Variable levels/classifications
Hit and run	Dependent	1: Hit and run happened; 2: Hit and run did not happened
Other vehicle’s intent	Independent	1: Going straight ahead; 2: Turning right; 3: Turning left; 4: Leaving a driveway; 5: 'U' turning; 6: Changing lanes; 7: Overtaking; 8: Merging; 9: Reversing; 10: Parking or unparking; 11: Parked legally; 12: Parked illegally; 13: Stationary accident; 14: Stationary broken down; 15: Other stationary; 16: Slow/stopping; 17: Out of control; 18: Wrong way; 19: Not known
Bicyclist’s intent	Independent	1: Going straight ahead; 2: Turning right; 3: Turning left; 4: Leaving a driveway; 5: 'U' turning; 6: Changing lanes; 7: Overtaking; 8: Merging; 9: Reversing; 10: Parking or unparking; 11: Parked legally; 12: Parked illegally; 13: Stationary accident; 14: Stationary broken down; 15: Other stationary; 16: Slow/stopping; 17: Out of control; 18: Wrong way; 19: Not known
Traffic control (other vehicle’s approach)	Independent	1: No control; 2: Stop go or Flashing lights; 3: Ped Light or Ped Crossing; 4: Roundabout; 5: Give way or stop sign; 6: Other; 7: Unknown
Traffic control (bicyclist’s approach)	Independent	1: No. control; 2: Stop go or Flashing lights; 3: Ped. Light or Ped. Crossing; 4: Roundabout; 5: Give way or stop sign; 6: Other; 7: Unknown

Variables	Dependent/ independent	Variable levels/classifications
Location type	Independent	If location type is intersection =1, Otherwise =0
Bicyclist's age	Independent	1: <=14; 2: 15-17; 3: 18-25; 4: 26-45; 5: 46-65; 6: >65
Speed zone	Independent	1: 40km/hr; 2: 50km/hr; 3: 60km/hr; 4: >=75km/hr; 5: Other; 6: Not Known
Crash time	Independent	1: Dark AM (00:00AM-6:00AM); 2: Morning Peak (6:00AM-9:00AM); 3: Morning Off Peak (9:00AM-4:00PM); 4: Afternoon Peak (4:00PM-7:00PM); 5: Afternoon Off-Peak (7:00PM-11:59PM)
Road geometry	Independent	1: cross intersection; 2: 'T' Intersection; 3: Other intersection; 4: Not at intersection; 5: Other
Helmet use (for bicyclist)	Independent	1: Crash helmet worn; 2: Crash helmet not worn; 3: Not appropriate; 4: Not known
Road surface (bicyclist's approach)	Independent	1: Paved; 2: Unpaved; 3: Gravel; 4: Not known
Road surface (other vehicle's approach)	Independent	1: Paved; 2: Unpaved; 3: Gravel; 4: Not known
Lighting condition	Independent	1: Day; 2: Dask/Dawn; 3: Dark; 4: Unknown
Melbourne/greater Melbourne/others	Independent	1: Melbourne; 2: Greater Melbourne; 3:Others
Bicyclist's gender	Independent	1: Male; 2: Female; 3: Unknown
Crash severity	Independent	1: Not fatal or serious injury; 2: Fatal or serious injury

For a contingency table that has r rows and c columns, the chi-square test could be thought of as a test of independence. In a test of independence the null and alternative hypotheses are:

Ho: The two categorical variables are independent.

H1: The two categorical variables are related.

We used the Equation (1) for computing the value of chi-square statistics.

$$\chi^2 = \sum \frac{(f_o - f_e)^2}{f_e} \quad (1)$$

Here, f_o is the frequency of the observed data and f_e is the frequency of the expected values (Levine et al. 2008). The expected frequency for each cell in the contingency table is computed as the product of its total row and total column divided by the overall sample size.
The calculated value is then compared with the critical value with (c-1)(r-1) degrees of freedom at the 95% confidence level. If the calculated value is greater than the critical value, then the null hypothesis would be rejected. In this study, the Pearson Chi-square test is undertaken using the cross-tab function in SPSS. Table 2 presents the results of Pearson Chi-Square test for the crash attributes listed in Table 1.

In the second step, a Binary Logistic Regression model is developed to identify the significant variables as well as the relative importance of the significant variables. Binary Logistic Regression model is a type of Generalized Linear Regression models (Washington et al. 2011). The probability of crash i, P_i (for i = 1, 2, ..., N) occurring at an intersection (y_i=1) would be given by:

$$p_i = \frac{EXP(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + ... + \beta_k X_{k,i})}{1 + EXP(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + ... + \beta_k X_{k,i})} \quad (2)$$

Where, β_0 is the model constant, β_1, ... , β_k are the unknown parameters associated with independent variables X_k, k= 1, ..., K is the set of independent variables, i = 1, …., N is the set of observations.

This model describes the relationship between a binary dependent variable and a number of independent variables (Washington et al. 2011). The best estimate of β could be obtained by maximising the log likelihood function as follows:

$$LL(\beta) = \sum_{i=1}^{n} \{ y_i \ln(P_i) + (1 - y_i) \ln(1 - P_i) \} \quad (3)$$

4. Analysis Results

As mentioned above, two-step statistical analysis is carried out in this study. The results of analysis are outlined in the following sub-sections.

4.1. Pearson Chi-Square test

Table 2 illustrates that the majority of variables are associated with the dependent variable. As shown in this table, speed zone, bicyclist's intent, road surface, location type, helmet use (for bicyclist) and whether crash took place in Melbourne, Greater Melbourne or other places in Victoria did not affect the dependent variable significantly. The effects of the rest of variables are significant with 90 percent level of confidence. Although the results of Pearson Chi-Square test revealed that bicyclist's intent and helmet use (for bicyclist) are not significant variables, these variables entered into the Binary Logistic Regression model as they considered as important variables which could influence the hit and run action.

Table 2: Results of the Pearson Chi-Square test.

Dependent Variable	Explanatory Variables	Significance level (Pearson Chi-Square test)
Hit and run	Speed zone	**0.648**
	Lighting condition	0.000
	Traffic control (other vehicle's approach)	0.000
	Traffic control (bicyclist's approach)	0.000
	Crash time	0.000
	Bicyclist's intent	**0.252**
	Other vehicle's intent	0.000

Dependent Variable	Explanatory Variables	Significance level (Pearson Chi-Square test)
	Road surface (bicyclist's approach)	**0.138**
	Road surface (other vehicle's approach)	**0.591**
	Location type	**0.396**
	Helmet use (for bicyclist)	**0.122**
	Location type	0.084
	Bicyclist's gender	0.005
	Bicyclist's age	0.000
	Crash severity	0.000
	Melbourne/greater Melbourne/others	**0.584**

In the next subsection, statistical modelling using Binary Logistic Regression model is developed to explore the significant variables as well as the relative importance of the significant variables.

4.2. Binary Logistic Regression model

Developing Binary Logistic Regression model will help identify the effect of different crash variables on "hit and run" action in Greater Melbourne. In this study, Binary Logistic Regression model is developed using the significant variables identified utilizing Pearson Chi-Square test as well as those variables which are not found to be significant using Pearson Chi-Square test but considered as important variables based on engineering judgment.

SPSS statistical analysis package is utilized to develop the Binary Logistic Regression model. Table 3 shows the results of the Binary Logistic Regression model. In this table, model parameters are estimated for possibility of not being involved in a hit and run crash. It can be seen in Table 3 that the significant attributes are crash time, bicyclist's age and gender, helmet use (for bicyclist), other road user's intent, bicyclist's intent, traffic control (other road user's approach), traffic control (bicyclist's approach) and crash severity.

Results of Binary Logistic Regression model revealed that the likelihood of hit and run bicycle crashes is higher in dark AM and PM times, which are 0:00 to 6:00 AM and 7:00 to 11:59 PM, with odds ratio of 1.00 and 1.70, respectively. These results are reasonable as traffic volume and road environment are more appropriate for hit and run action in dark AM and PM times. On the other hand, likelihood of hit and run bicycle crashes is lower for morning and afternoon peak hours, which are 6:00 to 9:00 AM and 4:00 to 7:00 PM, with odds ratio of 3.42 for both time periods.

The effect of bicyclist's age and gender on bicycle hit and run crashes show that female bicyclists are less likely to be involved in a hit and run bicycle crashes (with odds ratio of 1.39 compared to males with odds ratio of 1.00). The results also illustrate that bicyclists aged less than 14 years old are less involved in hit and run crashes compared to other age groups (odds ratio = 1:00) and for bicyclists aged between 15 and 17 years old the possibility of being involved in a hit and run crash is more than other age groups (odds ratio = 0.38). Results from model also show that there is no major difference in likelihood of being involved in a hit and run crash among bicyclists aged more than 18 years old (approximate odds ratio = 0.6).

Bicyclist's helmet use is also a significant variable in the Binary Logistic Regression model. Model parameters show that bicyclists who did not use helmet are less involved in hit and run crashes (with odds ratio of 1.65 compared to odds ratio of 1.00 which is for bicyclists who used helmet). This is an interesting result as using helmets generally reduces the injury severity of bicyclists. This result is consistent with the relationship of crash severity with possibility of hit and run crash for bicycle crashes in Victoria, Australia. The model parameters show that hit and run crashes are more associated with property damage only and minor injury crashes with odds ratio of 1:00 in comparison with fatal and serious injury crashes with odds ratio of 2.05.

Traffic control type for both bicyclist and other vehicle's approach are two other significant variables affecting the hit and run action in bicycle crashes. Estimated model parameters (see Table 3) reveal that for both bicycles and other road users, the hit and run crash are more likely to take place at mid-blocks in which no control is available (with odds ratio of 1:00 for both user types in comparison with odds ratio of 4.50, 1.42, and 1.85 for other levels of traffic control for other road user and 2.08 for other level of traffic control for bicyclist). Furthermore, Table 3 shows that roundabouts have the least effect on the likelihood of being involved in a hit and run bicycle crash for traffic control type of other road user (odds ratio = 4.50). Moreover, give way/stop sign is associated with the minimum likelihood of being involved in a hit and run crash for bicyclists (odds ratio = 2.08).

Table 3: Results of the Binary Logistic Regression model.

Output Variable	Explanatory Variables[a]	Description/variable levels	Rank (change in log-likelihood ratio)	Significance level (Wald statistic)	Count (Percentage)	Parameters (β)	Odds ratio (exp. β)
The crash is not a hit and run crash	Crash Time	0:00 AM to 6:00 AM (ref)	3	-	175 (2.5%)	0	1.00
		6:00 AM to 9:00 AM		<0.001	1833 (26.3%)	1.23	3.42
		9:00 AM to 4:00 PM		<0.001	2505 (36.0%)	1.06	2.89
		4:00 PM to 7:00 PM		<0.001	1856 (26.7%)	1.23	3.42
		7:00 PM to 11:59 PM		0.017	593 (8.5%)	0.53	1.70
	Bicyclist's age	Less than or equal to 14 years old (ref)	5	-	779 (11.2%)	0	1.00
		15 to 17 years old		<0.001	458 (6.6%)	-0.98	0.38
		18 to 25 years old		0.003	1007 (14.5%)	-0.55	0.58
		26 to 45 years old		0.004	3254 (46.7%)	-0.48	0.62
		46 to 65 years old		0.003	1240 (17.8%)	-0.53	0.59
		More than 65 years old		0.073	224 (3.2%)	-0.50	0.60
	Bicyclist's gender	Male (ref)	9	-	5332 (76.6%)	0	1.00

Output Variable	Explanatory Variables[a]	Description/variable levels	Rank (change in log-likelihood ratio)	Significance level (Wald statistic)	Count (Percentage)	Parameters (β)	Odds ratio (exp. β)
		Female		0.002	1601 (23.0%)	0.33	1.39
	Helmet use (for bicyclist)	Helmet worn (ref)	8	-	5268 (75.7%)	0	1.00
		Helmet not worn		0.003	625 (9.0%)	0.50	1.65
	Other road user's intent	Going straight ahead (ref)	1	-	2517 (36.1%)	0	1.00
		Turning right		<0.001	1367 (19.6%)	1.20	3.30
		Turning left		0.037	979 (14.1%)	0.26	1.30
		Leaving a driveway		<0.001	476 (6.8%)	1.27	3.55
		Overtaking		0.072	40 (0.6%)	-0.69	0.50
		Parking or un-parking		<0.001	169 (2.8%)	1.66	5.28
		Parked legally		<0.001	24 (0.3%)	1.20	7.37
		Stationary (not accident or broke down)		<0.001	165 (2.4%)	2.12	8.36
		Slow/stopping		0.058	51 (0.7%)	1.39	4.00
		Not known		<0.001	216 (3.1%)	-1.81	0.16
		No control (ref)	7	-	4297	0	1.00

Output Variable	Explanatory Variables[a]	Description/variable levels	Rank (change in log-likelihood ratio)	Significance level (Wald statistic)	Count (Percentage)	Parameters (β)	Odds ratio (exp. β)
					(61.7%)		
	Traffic control (other vehicle's approach)	Roundabout		0.023	575 (8.3%)	1.50	4.50
		Give way or stop sign		0.022	850 (12.2%)	0.35	1.42
		Unknown		0.096	294 (4.2%)	0.62	1.85
	Traffic control (bicyclist's approach)	No control (ref)	6	-	4678 (67.2%)	0	1.00
		Give way or stop sign		0.001	462 (6.6%)	0.73	2.08
	Bicyclist's intent	Going straight ahead (ref)	4	-	5866 (84.3%)	0	1.00
		Turning right		0.014	336 (4.8%)	0.53	1.70
		Leaving a driveway		0.013	85 (1.2%)	2.53	12.62
	Crash severity	Not fatal or serious injury crash (ref)	2	-	4713 (67.7%)	0	1.00
		Fatal or serious injury crash		<0.001	2249 (32.3%)	0.72	2.05
	Constant	-	-	0.008	-	0.66	1.94
Model Log Likelihood	Beginning	-2699.329					
	Final model	-2012.933					
Observations	6962						

a This column presents significant variable levels

Finally, the intent of bicyclists and the other drivers involved in the crash are other significant variables in the Binary Logistic Regression model. Model results illustrated that “overtaking”, “going straight ahead” and “turning left” are the other vehicle’s manoeuvres that are associated with high possibility of being involved in a hit and run crash (odds ratio of 0.50, 1.00 and 1.30 respectively). In addition, vehicles which are stationary, parked legally and vehicles that are parking or unparking at the time of crash are less likely to be involved in a hit and run bicycle crash (odds ratio of 8.36, 7.37, and 5.28 respectively). Regarding the bicyclist’s intent, going straight ahead and turning right increases the possibility of being involved in a hit and run crash (odds ratio of 1:00 and 1.70 respectively). Leaving the drive way (bicyclist) is associated with least possibility of being involved in a hit and run crash for (odds ratio = 12.62).

The relative importance of the variables in the developed Logistic Regression Model is also presented in the fourth column of the Table 3. This column presents the ranking of the variables in terms of the change in the value of likelihood ratio function (see Equation 3) that is occurred due to the variable. Based on this criterion, other road user’s intent is ranked as the first variable which has the most effect on the outcome variable. This is followed by crash severity, crash time, bicyclist’s intent, bicyclist’s age, traffic control for bicyclist’s approach, traffic control for other vehicle’s approach, helmet use (for bicyclist) and bicyclist’s gender.

5. Summary and Conclusion

Increasing the number of hit and run actions will result is increasing the severity of crash as a result of the delay in receiving medical help. Several studies have been conducted in order to find the effect of transport variables on this offence. Those studies considered the hit and run crashes either for pedestrian accidents or in general for other road users. They did not conduct separate investigation to understand the influence of different crash attributes on the hit and run act for the road crashes in which at least one cyclist is involved.

This study investigated the effect of crash attributes on the hit and run act in Victoria, Australia. In this study, two-step analysis has been conducted on the Victorian database to identify the effect of different variable on the Hit and run crashes in which at least one bicyclist is involved. In the first step, a Chi-Square test is performed to find out the significant independent variables. In the second step, a Binary Logistic Regression model is developed to explore the relative importance of the significant variables.

The results of the analysis showed that crash time, bicyclist’s age and gender, helmet use (for bicyclist), other road user’s intent, bicyclist’s intent, traffic control (other road user’s approach), traffic control (bicyclist’s approach) and crash severity are the significant variables in the Binary Logistic Regression model. Model parameters showed that the likelihood of hit and run crashes increased in the following conditions:

- Dark AM (0:00 to 6:00 AM) and dark PM (7:00 to 11:59 PM) time periods,
- Male bicyclists are involved in the crash,
- Bicyclists aged between 15 and 17 are involved in the crash,
- Bicyclists who used helmets are involved in the crash,
- There is property damage only or minor injury crash,
- Control type is “no control” for both bicyclist and other vehicle approaches,
- Other vehicle’s intent before crash is “going straight ahead”, “overtaking” and “turning left”,
- Bicyclist’s intent is “going straight ahead” and “turning right”.

Results of this study improved the understanding of crash parameters affecting bicycle hit and run crashes. Using the results from this research, some useful countermeasures could be designed to reduce the likelihood of this offensive action.

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