

Factors contributing to crashes at intersections and mid-blocks: Study of two-vehicle crashes at Australian Capital Territory

Sareh Bahrololoom¹, Richard Tay¹, Clare D'Souza¹, Amir Sobhani²

1 School of Business, Latrobe University, Victoria, Australia

2 Institute of Transport Studies, Monash University, Victoria, Australia

Email for correspondence: sbahrololoom@students.latrobe.edu.au

Abstract

Intersections are recognized as being among the most hazardous locations on the roads. Therefore, many jurisdictions around the world have set specific targets for the reduction in the number of deaths and serious injuries resulting from crashes at intersection. To achieve these goals and enhance road safety require a better understanding of the factors contributing to crashes at these hazardous locations in order to develop more targeted countermeasures. This study examines the effects of traffic characteristics, roadway design, vehicle features, collision types and road user characteristics on two-vehicle crashes at intersections compared to non-intersections in the Australian Capital Territory. These factors will be explored using chi-square tests and subsequently modelled using the binary logistic regression model. The results showed that the distribution of crash types is different for intersections and mid-blocks. We found that several roadway, environment, traffic, and crash characteristics had differential effects on intersections and mid-block crashes.

Key Words: Traffic Safety, Intersections, Mid-blocks, Number of Crashes, Severity of Crashes

1. Research Background

Road safety has been focus of researchers and authorities for decades. One important part of road safety research is to improve our understanding of the factors affecting safety performance of different road locations. Literature review of road safety research shows that many studies have been conducted to understand main factors affecting number and severity of crashes at different road locations (Golob et al. 1988; Turner and Nicholson 1998; Chin and Quddus 2003; Yan et al. 2005; Haung et al. 2008; Das et al. 2009; Das and Abdel-Aty 2010; Das and Abdel-Aty 2011). Intersections are a common place for crashes. This can be due to the number of different conflicting manoeuvres and/or their design characteristics. Furthermore, severe crashes, such as angle crash, are likely to occur at intersections (Abdel-Aty and Keller, 2005). Several studies have been conducted to find out the main factors affecting number and severity of crashes at intersections. Abdel-Aty and Keller (2005) used ordered probit model and tree-based regression method to find out the main variables affecting crash severity at intersections. Wong and Li (2007) used Poisson regression and negative binomial regression models to explore the relationship between number and severity of crashes and road and environmental characteristics at signalized intersections. Wang and Abdel-Aty (2008) used generalized estimating equations (GEE) with the negative binomial as the link function to explore the effect of human, vehicle and road and environmental characteristics on number of crashes for different left turn patterns at

signalized intersections. Literature review of safety analysis shows that there are a number of studies carried out to explore safety of intersections and non intersections (Roudsari et al. 2007; Moore et al. 2011). Abdel-Aty (2003) compared the factors affecting crash severity for intersections and non-intersections. He has investigated the effect of human, vehicle and road and environmental characteristics on crash severity and compared the significant variables at intersections and non-intersections.

In Summary, although several studies carried on exploring the factors affecting number and severity of crashes at intersections, there is not enough consideration to compare factors affecting crash at intersections and mid-blocks in previous studies. This study examines the effects of road and environment characteristics as well as human and vehicle characteristics on two-vehicle crashes at intersections compared to non-intersections in the Australian Capital Territory.

The next section of this paper outlines the data base used in this study. Then, the data analysis method utilized in this study is explained. The data analysis process is outlined next. This is followed by discussion of results and conclusion.

2. Data

Australian Capital Territory (ACT) crash data has been used in this study. This data base includes two separate spreadsheets for intersections and mid-blocks. It contains the related data of crashes occurred on ACT urban road network in 2010 and 2011. Information for crashes in these two years has been presented in two separate spread-sheets. The total number of intersection crashes is 9445 and the total number of mid-blocks crashes is 6778. The ACT data for 2011 is used in this study.

In this study these spread sheets have been combined for intersections and mid-blocks in order to form one data base for data analysis. Then, two-vehicle crashes have been extracted from the data base. Table 1 outlines the variables of the combined data base.

3. Data Analysis Method

Previous section outlined the database used in this study. This section explains the statistical methods utilized to analyse the data.

In the combined data base, the dependent variable is “intersection/mid-block” which indicates whether the crash takes place at intersection or mid-block. In this study two-step analysis is carried out to explore the factors affecting crash occurrence at intersections and mid-blocks.

1. In the first step a Chi-Square test is performed to find out the significant independent variables (see Table 1) influencing the dependent variable (“intersection/mid-block” variable). The Chi-Square test is carried out using Pearson Chi-Square test (Levine et al. 2008).
2. In the second step a Binary Logistic Regression model is developed in order to explore the relative importance of the significant variables. The significant variables affecting the crash location (intersection/mid-block) are also studied using this model.

Binary Logistic Regression model is a type of Generalized Linear Regression models in the form of Equation 1 (Washington et al. 2011).

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

Factors contributing to crashes at intersections and mid-blocks: Study of
two-vehicle crashes at Australian Capital Territory

Table1: Crash variables in the combined data base

Variables	Levels
Accident Type	1: Head on collision, 2: Rear end collision, 3: Right angle collision, 4: Right turn into oncoming vehicle, 5: Side swipe collision, 6: Others
Road Condition	1: Good dry surface, 2: Loose surface, 3: Muddy or oily surface, 4: Snow or ice, 5: Unknown, 6: Wet surface
Fixed Object Struck	1: Building or structure, 2: Guide post, 3: Kerb or guard rail, 4: Light or tele-pole, 5: Not Applicable, 6: Other, 7: Sign or signal pole, 8: Tree
Fixed Object Located On	1: East side of road, 2: Island, 3: Median, 4: North side of road, 5: Null, 6: Other, 7: South side of road, 8: Unknown, 9: West side of road, 10: Not applicable
Weather Condition	1: Fine, 2: Rain, 3: Cloudy, fog or smoke, 4: Others
Intersection/Mid-Block Location Type	1: Cross intersection, 2: Multiple intersections, 3: Other, 4: Roundabout, 5: T intersection, 6: Y intersection, 7: Median opening, 8: Non median opening
Traffic Control Code	1: Control not operated, 2: Give way sign, 3: Marked pedestrian crossing, 4: Other, 5: Police, 6: School crossing, 7: Stop sign, 8: Traffic lights, 9: Uncontrolled, 10: Unknown
Lighting Condition	1: Dark - good street lighting, 2: Dark - no street lights, 3: Dark - poor street lighting, 4: Daylight, 5: Semi-darkness, 6: Unknown
Road Type	1: Bridge, 2: Construction site, 3: Driveway or lane, 4: Normal road, 5: Other off road, 6: Parking area, 7: Private property, 8: Ramp, 9: Commuter cycle way, 10: Null
Road Angle	1: Curve (severe), 2: Curve (Slight), 3: Straight, 4: Not applicable, 5: Null
Road Grade	1: Crest, 2: Level or slight grade, 3: Steep grade, 4: Unknown
Vehicle1 Lane Code	1: Straight lane, 2: Left-turn lane, 3: Right-turn lane, 4: Merge lane, 5: Other, 6: Unknown
Vehicle1 position	1: Approaching intersection, 2: Into driveway, 3: Not related to intersection, 4: Out of driveway, 5: Unknown, 6: Within intersection
Vehicle1 Movement	1: Left-turn, 2: Right-turn, 3: Straight ahead, 4: Overtaking left side, 5: Overtaking right side, 6: Other, 7: Unknown
Vehicle1 Action	1: Changing lane, 2: Parking (into/out), 3: Unknown, 4: Other, 5: Out of control, 6: Proceeding normally, 7: Slowing, 8: Stopped
Driver1 License Class	1: Any motor cycle, 2: Heavy bus, 3: Car, 4: Heavy truck, 5: Light truck, 6: Light bus, 7: Unknown, 8: Null
Driver 1 Gender	1: Female, 2: Male, 3: Null, 4: Unknown
Vehicle1 Type	1: Bus, 2: Car or station wagon, 3: Truck, 4: Taxi, 5: Other, 6: Unknown
Vehicle1 Visibility Restriction	1: Obstructed, 2: Not obstructed, 3: Null
Driver 1 Age	1: Missed, 2: 16-25, 3: 26-45, 4: 46-65, 5: >65
Vehicle2 Lane Code	1: Straight lane, 2: Left-turn lane, 3: Right-turn lane, 4: Merge lane, 5: Other, 6: Unknown
Vehicle2 Position	1: Approaching intersection, 2: Not related to intersection, 3: Into/out of driveway, 4: Unknown, 5: Within intersection, 6: Null
Vehicle2 Movement	1: Left-turn, 2: Right-turn, 3: Straight ahead, 4: Overtaking left side, 5: Overtaking right side, 6: Other, 7: Unknown
Vehicle2 Action	1: Changing lane, 2: Parking (into/out), 3: Unknown, 4: Other, 5: Out of control, 6: Proceeding normally, 7: Slowing, 8: Stopped
Driver 2 License Class	1: Any motor cycle, 2: Heavy bus, 3: Car, 4: Heavy truck, 5: Light truck, 6: Light bus, 7: Unknown, 8: Null
Driver 2 Gender	1: Female, 2: Male, 3: Null, 4: Unknown
Vehicle2 Type	1: Bus, 2: Car or station wagon, 3: Truck, 4: Taxi, 5: Other, 6: Unknown
Vehicle2 Visibility Restriction	1: Obstructed, 2: Not obstructed, 3: Null
Driver 2 Age	1: Missed, 2: 16-25, 3: 26-45, 4: 46-65, 5: >65

Where β_0 is the model constant and β_1, \dots, β_k are the unknown parameters associated with independent variables ($X_k, k=1, \dots, K$ the set of independent variables).

This model describes the relationship between a binary dependent variable and a number of independent variables (Washington et al. 2011). In this study since the “intersection/mid-block variable” is a binary output variable we utilize Binary Logistic Regression for developing the model.

4. Data Analysis Results

4.1 Pearson chi-square test

Pearson chi-square test is carried out using SPSS software. Table 2 summarises the results of the Pearson chi-square test. The results show that only “weather Condition” and “Driver 1 Age” do not have significant effect on output variable. All the other variables significantly influence the dependent variable based of Pearson chi-square test with 95% level of confidence.

Table2: Results of Pearson chi-square test

Dependent Variable	Explanatory Variables	Significance Level (Pearson Chi-Square test with 95% level of confidence)
Intersection/Mid-Block	Accident Type	<0.0001
	Road Condition	0.010
	Fixed Object Struck	<0.0001
	Fixed Object Located On	<0.0001
	Weather Condition	0.547
	Intersection/Mid-Block Location Type	<0.0001
	Traffic Control Code	<0.0001
	Lighting Condition	<0.0001
	Road Type	<0.0001
	Road Angle	<0.0001
	Road Grade	<0.0001
	Vehicle1 Lane Code	<0.0001
	Vehicle1 position	<0.0001
	Vehicle1 Movement	<0.0001
	Vehicle1 Action	<0.0001
	Driver1 License Class	0.016
	Driver 1 Gender	<0.0001
	Vehicle1 Type	<0.0001
	Vehicle1 Visibility Restriction	<0.0001
	Driver 1 Age	0.572
	Vehicle2 Lane Code	<0.0001
	Vehicle2 Position	<0.0001
	Vehicle2 Movement	<0.0001
	Vehicle2 Action	<0.0001
	Driver 2 License Class	<0.0001
	Driver 2 Gender	<0.0001
	Vehicle2 Type	<0.0001
	Vehicle2 Visibility Restriction	<0.0001
	Driver 2 Age	0.050

In the next step the significant variables identified using Pearson chi-square test are considered as independent variables of the Binary Logistic Regression model.

4.2 Binary Logistic Regression model

SPSS software is utilized to run the Binary Logistic Regression Model (BLRM). The “Intersection/Mid-Block” which is a binary output variable is the dependent variable in the model. The variables which were significant based on Pearson chi-square test are entered as the explanatory variables of the model.

The model is calibrated using forward step-wise method. The significance of independent variables for including in the model at each step is indicated using likelihood ratio method. The significance of the variable levels for entering into the model is assessed using Wald statistics. The calibration process is carried out using 70% of the data that is randomly selected. The remained part of the data (30%) is used to validate the model.

The modelling results shows a high goodness-of-fit level based on Omnibus test of model coefficients, Cox and Snell R Square, Nagelkerke R Square and Hosmer and Lemeshow test of model goodness-of-fit. Table 3 and Table 4 outline the results of the classification table for calibration and validation of the model. These tables show that the model predicts the dependent variable correctly for more than 98% of the cases.

Table 3: Classification table for model calibration

Selected Cases (70%)			
Observed	Predicted		
	Intersection	Midblock	Percentage Correct
Intersection	1648	11	99.3%
Mid-Block	11	835	98.7%
Overall Percentage			99.1%

Table 4: Classification table for model validation

Unselected Cases (30%)			
Observed	Predicted		
	Intersection	Midblock	Percentage Correct
Intersection	729	8	98.9%
Mid-Block	12	339	96.6%
Overall Percentage			98.2%

Table 5 shows the results of model calibration and model parameter estimates. Model parameters show that “Accident Type”, “Vehicle 1 Movement”, “Vehicle 1 Visibility Restriction”, “Vehicle 2 Position”, “Vehicle 2 Movement”, “Vehicle 2 Action”, “Driver 2 Age”, and “Road Angle” are the significant independent variables in the model. The result of the Binary Logistic Regression model reveals the following conclusions:

- Rear end and side swipe collisions are more likely to happen at mid-blocks; while, there is more possibility to have right angle and right turn into oncoming vehicle collisions at intersections.
- According to vehicles movements (“Vehicle 1 Movement” and “Vehicle 2 Movement”) it can be seen that overtaking from right side is one of the main causes of mid-block crashes; however, model parameters show that for “Vehicle 1 Movement” right turning and for “Vehicle 2 Movement” moving straight ahead are the most possible

Factors contributing to crashes at intersections and mid-blocks: Study of
two-vehicle crashes at Australian Capital Territory

causes of crashes at intersections. This result confirms high possibility of right turn into oncoming vehicle crash to take place at intersections.

- The model parameters show that if the visibility of the driver is not obstructed the possibility of crash is lower at mid-blocks.

Table 5: Model parameters

Level of The Dependent variable (i)	Independent variable ($X_{k,i}$)	Significance Level (Wald Statistic)	Level of The Variable	Parameters (β_i)	Odd Ratio (Exp β_i)
Mid-Block	Accident Type	<0.0001	Rear end collision	1.938	6.948
			Right angle collision	-6.372	0.002
			Right turn into oncoming vehicle	-3.589	0.028
			Side swipe collision	4.705	110.463
			Others	-3.166	0.042
	Vehicle 1 Movement	0.007	Right turn	-1.520	0.219
			Straight ahead	2.227	9.276
			Overtaking left side	1.467	4.335
			Overtaking right side	1.814	6.134
			Other	3.742	42.193
	Vehicle 1 Visibility Restrictions	0.003	Not obstructed	-1.730	0.177
	Vehicle 2 Position	<0.0001	Not related to intersection	7.23	1380.889
			Into/out of driveway	9.076	8744.263
	Vehicle 2 Movement	0.013	Right turn	0.379	1.461
			Straight ahead	-0.422	0.656
			Overtaking left side	-1.005	0.366
			Overtaking right side	2.574	13.115
			Other	3.741	42.127
	Vehicle 2 Action	<0.0001	Parking (into/out)	-2.610	0.074
			Unknown	-2.213	0.109
			Other	-0.577	0.561
			Out of control	0.496	1.642
			Proceeding normally	2.289	9.868
			Slowing	-1.429	0.239
	Driver 2 Age	0.004	Stopped	1.404	4.073
			16-25 years old	2.034	7.641
			26-45 years old	2.966	19.416
			46-65 years old	2.649	14.146
Road Angle	0.006	>65 years old	-2.116	0.121	
		Curve (slight)	5.576	264.087	
Constant	0.001	Straight	5.182	178.127	
		Constant	-11.945	0.0001	

Factors contributing to crashes at intersections and mid-blocks: Study of
two-vehicle crashes at Australian Capital Territory

- The related model parameters for “Vehicle 2 Position” confirm higher possibility of crash for vehicles driving into or out of driveways at mid-blocks.
- Considering “Vehicle 2 Action” the second vehicle is more likely to proceed normally or be stopped in mid-block crashes. On the other hand, the least number of crashes have been reported when the second vehicle is going into/out of parking.
- Drivers aged between 26 and 45 are more likely to be involved in mid-block crashes; while, the possibility of being involved in intersection crashes is more for older (>65) and younger (16-25) drivers. These results could be achieved due to lower driving performance of the former and low experience of the latter.
- Mid-block crashes are more likely to happen at straight road sections and slight curves. Therefore, it can be realized that presence of severe curve increases the possibility crashes at intersections.

The above results provide useful information for road safety authorities in order to understand main factors affecting intersection and non intersection crashes. Therefore, some appropriate countermeasures could be applied to improve safety performance of intersections and mid-blocks.

5. Conclusion

This study has outlined the understanding of factors affecting two-vehicle crashes occurred at intersections and non intersection in Australian Capital Territory. Australian Capital Territory (ACT) data base including related information about intersection and mid- block crashes has been used for data analysis. Data analysis has been conducted using Pearson chi-square test as well as Binary Logistic Regression Model. The significant variables have been identified using Pearson chi-square, and then a Binary Logistic Regression model has been developed to explore the relative importance of the variables.

The model parameter estimates showed that “Accident Type”, “Vehicle 1 Movement”, “Vehicle 1 Visibility Restriction”, “Vehicle 2 Position”, “Vehicle 2 Movement”, “Vehicle 2 Action”, “Driver 2 Age”, and “Road Angle” were the significant independent variables in the model.

Final results revealed that for mid-blocks:

- Rear end and side swipe crashes are more likely to take place.
- Overtaking from right side increases the possibility of mid-block crashes.
- The possibility of crash is lower if the driver vision is not obstructed.
- The possibility of crash is higher if driver moves into or out of the driveways.
- Drivers aged between 25 and 45 are more likely to have mid-block crashes.
- More mid-block crashes take place in straight and slight curves.

For intersections:

- Right angle and right turn into oncoming vehicle collisions are more likely to take place.
- Right turning movement for vehicle 1 and moving straight for vehicle 2 increase the possibility of intersection crashes.

Factors contributing to crashes at intersections and mid-blocks: Study of
two-vehicle crashes at Australian Capital Territory

- Drivers aged between 16 and 25 and drivers aged more than 65 are more likely to have intersection crashes.
- The possibility of intersection crashes increases in presence of severe curves.

The result of this study improve the understanding of the factors affecting intersection and mid-blocks crashes and enable road safety authorities to apply appropriate countermeasures to enhance roads safety level.

Acknowledgement:

Authors would like to acknowledge NRMA-ACT Road Safety Trust for their financial support in this research project.

References

Abdel-Aty, M. (2003). "Analysis of driver injury severity levels at multiple locations using ordered probit models." Journal of Safety Research **34**(5): 597-603.

Abdel-Aty, M. and J. Keller (2005). "Exploring the overall and specific crash severity levels at signalised intersections." Accident Analysis and Prevention **37**(3): 417-425.

Chin, H. C. and M. A. Quddus (2003). "Applying the random effect negative binomial model to examin traffic accident occurrence at signalised intersections." Accident Analysis and Prevention **35**(2): 253-259.

Das, A. and M. Abdel-Aty (2010). "A genetic programming approach to explore the crash severity on multi-lane roads." Accident Analysis and Prevention **42**(2): 548-557.

Das, A., M. Abdel-Aty and A. Pande (2009). "Using conditional Inference forests to identify the factors affecting crash severity on arterial corridors " Journal of Safety Research **40**(4): 317-327.

Das, A. and M. A. Abdel-Aty (2011). "A combined frequency–severity approach for the analysis of rear-end crashes on urban arterials." Safety Science **49**(8–9): 1156-1163.

Golob, T. F., B. Ruhl, H. Meurs and L. V. Wissen (1988). "An ordinal multi variate analysis of accident counts as functions of traffic approach volumes at intersections." Accident Analysis and Prevention **20**(5): 335-355.

Haug, H., C. H. Chor and M. M. Haque (2008). "Severity of driver injury and vehicle damage in traffic crashes at intersections: A baysian hierarchical analysis." Accident Analysis and Prevention **40**(1): 45-54.

Levine, D. M., D. F. Stephan, T. C. Krehbiel and M. L. Berenson (2008). Statistics for managers using microsoft excel. New Jersey, Pearson Education, Inc.

Factors contributing to crashes at intersections and mid-blocks: Study of
two-vehicle crashes at Australian Capital Territory

Moore, D. N., W. H. Schneider Iv, P. T. Savolainen and M. Farzaneh (2011). "Mixed logit analysis of bicyclist injury severity resulting from motor vehicle crashes at intersection and non-intersection locations." Accident Analysis & Prevention **43**(3): 621-630.

Roudsari, B., R. Kaufman and R. Nirula (2007). "Comparison of mid-block and intersection-related left turn collisions." Traffic injury prevention **8**(4): 393-397.

Turner, S. and A. Nicholson (1998). "Intersection Accident Estimation: The role of intersection location and Non-Collision flows." Accident Analysis and Prevention **30**(4): 505-517.

Wang, X. and M. Abdel-Aty (2008). "Analysis of left-turn crash injury severity by conflicting pattern using partial proportional odds models." Accident Analysis and Prevention **40**(5): 1674-1682.

Washington, S., M. G. Karlaftis and F. L. Mannering (2011). Statistical and Econometric Methods for Transportation Data Analysis. New York, United States, CRC Press.

Wong, S. C., N. N. Sze and Y.C.Li (2007). "Contributory factors to traffic crashes at signalised intersections in Hong Kong." Accident Analysis and Prevention **39**(6): 1107-1113.

Yan, X., E. Radwan and M. Abdel-Aty (2005). "Characteristics of rear-end accidents at signalised intersections using multiple logistic regression models." Accident Analysis and Prevention **37**(6): 983-995.