EFFECT OF NEIGHBOURHOOD STREET PATTERN ON MOTORCYCLE CRASH SEVERITY AT CALGARY

Shakil Mohammad Rifaat, Graduate Student
Dr. Richard Tay, AMA Chair in Road Safety
Dr. Alex De Barros, Assistant Professor
University of Calgary

INTRODUCTION

Motorcycles are often associated with high accident risk and higher injury severity. In Alberta, Canada, 59 riders were killed and 2152 were injured in motorcycle involved crashes during 2003-2005 (Alberta Transportation, 2006). To develop proper countermeasures, it is important to know the factors affecting the occurrence of motorcycle involved crashes and associated injury outcomes.

A number of studies have investigated the factors affecting motorcycle crash severity (Clarke et al, 2007; Haque et al, 2010; Kasantikul et al, 2005; Gabella et al, 1995; Conrad et al, 1996; Branas and Knudson, 2001; Savolainen and Mannering, 2007; Lapparent, 2006; Zambon and Hasselberg, 2006; Yannis et al, 2004; Li et al., 2009; Majdzadeh et al, 2008; Quddus et al, 2002; Savolainen and Mannering, 2007). These factors include: road design characteristics such as number of lanes, wide median, uncontrolled left turn, exclusive right-turn lane etc; riders characteristics and actions such as rider's age, gender, alcohol intoxication, speeding, use of helmet, loss of the control of motorcycle, right of way violation, traffic control signal violation etc; road characteristics such as local road, intersection, highways, environmental characteristics such as lighting condition, time of crashes and vehicle characteristics such as engine capacity, headlight, etc.

However, very few study have examined the effect of street pattern on crash severity. Recently, Rifaat and Tay (2009a, 2009b, 2009c, 2008) has undertaken a series of studies to identify the influence of street pattern on injury severity of different crashes involving two-vehicle, single vehicle and pedestrian and bicycle. As a part of their continuing efforts, this study examines how the different street patterns may affect the severity of motorcycle involved collisions. Besides street pattern, other factors related to road features, drivers' characteristics, crash characteristics, environment condition and vehicle attributes are also explored as control variables. In addition, this study will test whether our main finding is sensitive to the different statistical models used.

METHODOLOGY

Ordered Response Models

As the severity of a crash is ordinal in nature, many researchers have chosen to use the ordered probit or logit model because these models yield estimates that are consistent and efficient (Rifaat & Chin, 2007; Tay & Rifaat, 2007). The ordered logit model (OLM) is chosen for the analysis to ease of comparison with the other models used.

If the severity of a crash can be considered as an ordinal variable with m categories, the probability of a crash having a severity level j will be given by (Long 1997; Quddus et al. 2009):

$$\Pr(\mathrm{y_i} > j) = \mathrm{g}(\mathbf{X_i}\boldsymbol{\beta}') = \frac{\exp\left(\mathbf{X_i}\ \boldsymbol{\beta}' - \tau_j\right)}{1+\exp\left(\mathbf{X_i}\ \boldsymbol{\beta}' - \tau_j\right)}\ , \mathrm{j} = 1 \ldots, \mathrm{m} - 1$$

Where $\boldsymbol{X_i}$ is a $(k \times 1)$ vector of observed non-random explanatory variables; $\boldsymbol{\beta}$ is $(k \times 1)$ vector of unknown parameters to be estimated; m is the number of categories of the ordinal dependent variable. The parameters of the model $(\boldsymbol{\beta})$ and the cut-points $(\tau_1 and\ \tau_2)$ are estimated by the method of maximum likelihood (Long 1997).

An assumption in OLM is that the errors are homoskedastic. However, if they are heteroskedastic, the estimated parameters will be biased and inconsistent (Keele and Park 2006; Quddus et al. 2009) In order to deal with unequal error variances, Williams (2006) suggests the use of a heterogeneous choice model (HCM) shown below:

$$\Pr(y_i > j) = g\left(\frac{\boldsymbol{X_i}\boldsymbol{\beta}'}{\sigma_i}\right) = \frac{\exp(\frac{\boldsymbol{X_i}\boldsymbol{\beta}'}{\sigma_i} - \tau_j)}{1 + \exp(\frac{\boldsymbol{X_i}\boldsymbol{\beta}'}{\sigma_i} - \tau_j)}, j = 1, \ldots, m-1$$

$$ln\sigma_i = \boldsymbol{Z_i}\theta'$$

where $\boldsymbol{Z_i}$ would be a vector of explanatory variables that effected the error variance (σ_i). It should be noted that $\boldsymbol{Z}$ can either be a subset of $\boldsymbol{X}$ or a new set of variables not included in $\boldsymbol{X}$.

Another important assumption associated with the OLM regression is that the regression parameters are the same for different severity levels, known as the parallel-lines or proportional odds assumption. Hence, the slope coefficients do not vary over different alternative. This parallel-lines assumption could be violated in many cases. An alternate solution would be to employ a generalised ordered logit model (GOLM) which would not impose the constraint of parallel regressions (Fu 1998; Quddus et al. 2009). The unconstrained GOLM could be written as:

$$\Pr(y_i > j) = g(\boldsymbol{X_i}\boldsymbol{\beta}') = \frac{\exp(\boldsymbol{X_i}\boldsymbol{\beta}' - \tau_j)}{1 + \exp(\boldsymbol{X_i}\boldsymbol{\beta}' - \tau_j)}, j = 1, \ldots, m-1$$

Unlike the OLM, $\boldsymbol{\beta}$ would not be fixed across equations in GOLM. It should be noted that in the GOLM, the parallel-lines constraint would be relaxed for all the variables. This method would free all variables from the parallel-lines constraint, even though the assumption might be violated only by one or a few of the variables.

Considering that the parallel-lines assumption may be violated only by one or a few variables, a partial proportional odds model can be specified, for which one or more βs may differ across equations and others can be the same for all equations. The structural form of the partially constrained generalized ordered logit model (PC- GOLM) is:

$$\Pr(y_i > j) = \frac{\exp(\boldsymbol{X_{1i}\beta'_{1j}} + \boldsymbol{X_{2i}\beta'_2} - \tau_j)}{1 + \exp(\boldsymbol{X_{1i}\beta'_{1j}} + \boldsymbol{X_{2i}\beta'_2} - \tau_j)}, j = 1, \ldots, m-1$$

where the coefficients associated with a subset of independent variables $\boldsymbol{X2}$ would be the same across all values of j and the coefficients related to other independent variables $\boldsymbol{X1}$ would differ across some values of j . In our study, three ordered response models (OLM, HCM and PC-GOLM) will be applied to check whether our policy decision varies with the different models used.

Classification of Street Pattern

The street pattern in each community area in Calgary defined by The Census is classified using a scheme adapted from Southworth and Ben-Joseph (2003). The authors classified street patterns into five categories: gridiron, fragmented parallel, warped parallel, loops and lollipops, and lollipops on a stick. However, the fragmented parallel pattern was found in very few communities in Calgary and this category was merged with grid iron pattern since it contains mainly straight roadways. Also, the two street patterns with the lollipop designs were merged into one to simplify the classification scheme. Finally, a separate category called mixed pattern was created to allow for community areas with mixed design. Figure 1 shows an example of a community in each of the four categories.

Figure1: Types of Street Pattern in Calgary Community Areas

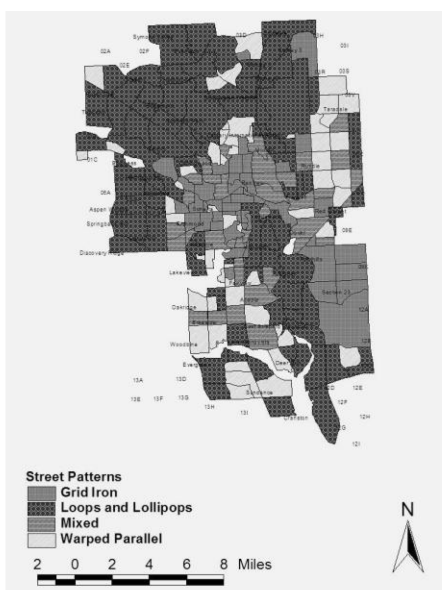
Warp parallel in Fairview

Gridiron in Forest Lawn

Loops and Lollipops in Citadel Mixed Pattern in Altadore

Of the 227 community areas, 46 are classified as grid-iron, 55 are warped parallel, 87 are loops and lollipops, and the remaining 39 are mixed pattern (Figure 2). After classifying street pattern in each community, crashes are mapped with street addresses using Arc View 3.2 which enable to identify the patterns of streets where crashes occurred.

Figure 2: Distributions of Street Patterns in Calgary



Data and Model Development

Motorcycle crash data from 2003 to 2005 for the City of Calgary was provided by Alberta Transportation. Crashes on arterials forming the boundaries of communities were excluded. Of the 466 crashes, 1.07% crashes were classified as fatal crashes, 48.93% are classified as injury crashes and the rest of them are property damage or no injury crashes. The severity of a crash was determined by the person with the most severe injury and a crash was considered as fatal if at least one person involved in the crash died within 30 days of collision. A crash was considered to be an injury crash if at least one person was injured and a property damage crash was defined as a crash associated with no injury but only damages to properties over $1000.

Two approaches were used to select appropriate factors for the models. The first approach used was to review similar research where these factors had been examined. The second option was to focus on local context to determine other variables that might have some influence on injury crashes. It should be noted that some important factors such as speed limit, road width, median width, shoulder width, AADT, etc., identified having significant effect on crash severity in previous studies, were not explored here because of the lack of information. After considering the missing values, 238 observations are used to develop models. Since most of the factors were recorded in categories, several dichotomous variables were formed from each factor in order to facilitate the estimation and interpretation of results. The estimates of the variables should be interpreted as relative to the omitted variable(s) of the factor they belonged.

After some preliminary analyses, 13 factors are retained in the final models and the descriptive statistics of the factors included in the final models were reported in Table 1. Some factors were tested and excluded in the final model reported because they were found to be statistically insignificant. These factors include time trend, day of week, driver age, road condition, traffic control condition, road alignment, environmental condition, road class, road surface condition, collision location, community type, licensing features etc.

Table1: Summary Statistics of Variables

Variables	Mean	Std Dev
Street Pattern		
Grid iron	0.319	0.467
Warped Parallel	0.118	0.323
Loops &lollipops	0.345	0.476
Mixed	0.218	0.414
Control Variables		
Special Road Location		
No Special Location	0.895	0.307
Parking Lot	0.067	0.251
Interchange Ramp	0.013	0.112
Bridge/Overpass	0.013	0.112
Service Road	0.008	0.091
Others	0.004	0.065
Unsafe Speed		
Yes	0.130	0.337
No	0.441	0.498
Not Available	0.429	0.496
Type of Vehicle		
Passenger Car	0.521	0.501
Pick-Up/Van	0.118	0.323
Minivan	0.130	0.337
Truck	0.038	0.191
Fixed Object	0.151	0.359
Others	0.042	0.201
Vehicle Repairable		
Yes	0.706	0.457
No	0.113	0.318
Unknown	0.181	0.386
Primary Event		
Struck Object	0.269	0.444
Rear End	0.206	0.405
Right Angle	0.126	0.333
Left Turn Across Path (LTAP)	0.164	0.371
Sideswipe	0.071	0.258

Off Road Right	0.034	0.181
Passing –Left Turn	0.042	0.201
Other Primary Event	0.088	0.284
Motorcyclist’s Sex		
Male	0.945	0.228
Motorcyclist’s Condition		
Normal	0.794	0.405
Alcohol Impaired	0.042	0.201
Other driver condition	0.164	0.371
Motorcyclist’s Action		
Riding Properly	0.420	0.495
Ran Off Road	0.071	0.258
Follow-too-Closely	0.084	0.278
Others	0.425	0.495
Time of day		
Peak	0.223	0.417
Off Peak	0.378	0.486
Night	0.399	0.491
Seasonal Condition		
Fall	0.261	0.440
Winter	0.218	0.414
Spring	0.197	0.399
Summer	0.324	0.469
Light Condition		
Daylight	0.761	0.428
Sunglare	0.008	0.091
Darkness	0.231	0.422
Province of Plate		
Other Provinces	0.025	0.157

RESULTS AND DISCUSSION

The estimation results were reported in Table 2. In general, the models fitted the data relatively well, with good goodness-of-fit statistics.

TABLE 2 Parameter Estimates of the Models

Variables	OLM	HCM	PC-GOLM	
			PDO-Injury	Injury-Fatal
Street Pattern (Ref: Grid-iron				
Warped Parallel	0.300	0.278	0.258	
Loops & lollipops	0.714*	0.782**	0.744*	
Mixed	0.421	0.456	0.419	
Control Variables				
Special Road Location				
Parking Lot	-1.265**	-1.252**	-1.260**	
Unsafe Speed				
Yes	2.199**	2.129***	2.100***	
Type of Vehicle				
Pick-Up/Van	-0.999**	-0.840*	-0.804*	
Truck	2.321**	2.615**	2.931**	
Vehicle Repairable				
Yes	-0.683*	-0.641*	-0.725**	
Primary Event				
Right Angle	0.895*	0.916*	0.940**	
LTAP	1.012**	1.052**	1.129**	
Motorcyclist's Sex				
Male	-1.663**	-1.668**	-1.688**	
Motorcyclist's Condition				
Alcohol Impaired	2.673**	3.218**	0.601	4.936**
Motorcyclist's Action				
Follow-too-Closely	-1.526**	-1.453**	-1.409**	
Time of day				
Peak	0.693*	0.671*	0.668*	
Seasonal Condition				
Winter	-1.025**	-1.035***	-1.026**	
Lighting Condition				
Darkness	0.784**	0 .760*	0.743*	
Province of Plate				
Other Provinces	3.494**	3.190**	3.062**	
Constant	-	-	1.824**	5.711**

cut-point1	-1.776**	-1.723*	-	-
cut-point2	4.581**	5.144**	-	-
Factors affecting the error variance				
Impaired by Alcohol	-	0.602	-	-
Model Statistics				
Observations	238	238	238	
Log-likelihood	-139.129	-138.659	-135.992	
Chi-Square	83.73	84.67	90	
P- value	<0.0001	<0.0001	<0.0001	
Note: & ** denote statistically significant at α = 0.10 & 0.05 For PCGOLM, variables with separate columns represent proportional odds relaxed; those with combined column represent constrained.				

Street Patterns

The main objective of our study was to identify the effect of different street patterns on the injury risks in motorcycle involved crashes. Compared with grid-iron pattern, all the other types of street patterns increased the risk of more severe injury but not all results are statistically significant. More specifically, only the loops and lollipops design was statistically significant in all models.

Altogether these results indicated that roads with less connectivity and frequent curves were not safer than traditional grid-iron road from motorcycle crash severity perspective. Perhaps the presence of frequent curves and loops in these limited access designs made them difficult to maneuver for motorcyclists. The poorer sight distances might make reducing speed during an impending collision more difficult. Also, there might be a higher chance of injury from falling off the motorcycles or losing control of vehicles.

From the modeling perspective, OLM, HCM and PC-GOLM models yielded the same results on the policy decision and the values of the estimated coefficients of the street pattern do not vary significantly from model to model. Hence, the standard ordered logit model appeared to be fairly robust to the violation of the proportional odds assumption.

.

Control Variables

While analyzing the effect of road characteristics on injury severity, we found that, as expected, crashes at parking lot were less prone to result in severe injury. Consistent with previous studies (Shankar and Mannering, 1996; Savolainen and Mannering, 2007; Pai et al, 2009; Li et al, 2009) our study found that speeding increased the probability of more severe injuries. Also, consistent with previous studies, collisions with trucks were associated with high risk of severe injury whereas, in contrast with previous findings (Savolainen and Mannering, 2007; Pai, 2009; Majdzadeh et a., 2008) collision with pickup were less likely to be harmful from injury perspective. Similar to findings in previous studies (Savolainen and Mannering, 2007; Pai and Saleh, 2007) we found that right angle crashes and left turn across path movements increased crash severity.

While exploring rider's characteristics, our study found that alcohol use increased the possibility of causing more severe injuries, a result that consistent with the findings of other studies (Savolainen and Mannering, 2007; Kasantikul et al, 2005; Shankar and Mannering, 1996; Gabella et al, 1995). Interestingly, male riders were involved in less injury crashes compared with their female counterparts. However, similar result was observed in some studies as well (Savolainen and Mannering, 2007; Quddus et al, 2002). As expected, riders who followed too closely to the vehicle ahead exacerbated the crash severity.

Consistent with Quddus et al.(2002), our study found that crashes during peak hours increased the likelihood of injury and fatality. Furthermore, a negative association was found between winter and crash injury, a result that was consistent with previous findings (Pai, 2009; Pai et al, 2009, Branas and Knudson, 2001). Our study also found that darkness was positively correlated with motorcycle crash severity which was consistent with the findings of other studies (Quddus et a., 2002; Pai, 2009; Li et al, 2009, Lapparent, 2006). Finally, as expected, relative to the locals, riders from other provinces were involved in crashes that resulted in more severe injury.

CONCLUSION

In conclusion, our study suggests that loops and lollipops types design is less safe than traditional grid pattern from motorcycle crash severity perspective. Perhaps the presence of curves, cul-de-sac and sight distance restrictions associated with those limited access design might be the reason of this result. Furthermore, this policy decision is not sensitive to the different ordered response models used.

REFERENCES

Branas, C. C., Knudson, M. M. ,2001. Helmet laws and motorcycle rider death rates. *Accident Analysis and Prevention*, 33(6), 641–648.

Clarke, D.D., Ward, P., Bartle, C., Truman, W., 2007. The role of motorcyclist and other driver behaviour in two types of serious accident in the UK. *Accident Analysis and Prevention,39,* 974-981

Conrad, P., Bradshaw, Y.S., Lamsudin, R., Kasniyah, N., Costello, C. (1996). Helmets, Injuries and Cultural Definitions: Motorcycle Injury in Urban Indonesia. *Accident Analysis and Prevention,* Volume. 28, No. 2, 193-200.

Fu, V., 1998. Estimating Generalized Ordered Logit Models. *Stata Technical Bulletin* 44: 27-30. In *Stata Technical Bulletin Reprints*, vol 8, 160-164. College Station, TX: Stata Press.

Gabella, B., Reiner, K. L., Hoffman, R. E., Cook, M., Stallones, L. ,1995. Relationship of helmet use and head injuries among motorcycle crash victims in El Paso County, Colorado, 1989– 1990. *Accident Analysis and PSafety_Jorevention*, 27(3), 363–369.

Haque, M.M., Chin, H.C., Huang, H., 2010. Applying Bayesian hierarchical models to examine motorcycle crashes at signalized intersections. *Accident Analysis and Prevention, 42*,203-212

Kasantikul, V., Quellet, J.V., Smith, T., Sirathranont, J., Panichabhongsw, V., 2005. The role of alcohol in Thailand motorcycle crashes. *Accident Analysis and Prevention, 37,* 357-366

Keele, L., Park, D., 2006, "Difficult choices: an evaluation of heterogeneous choice models", Working paper, Department of Political Science, Ohio State University. Available at http://www.nd.edu/~rwilliam/oglm/ljk-021706.pdf, Accessed on 18th July 2008.

Lapparent, M.D., 2006. Empirical Bayesian analysis of accident severity for motorcyclists in large French urban areas. *Accident Analysis and Prevention, 38,* 260-268.

Li, M.D., Doong, J.L., Huang, W.S., Lai, C.H., Jenga, M.C., 2009. Survival hazards of road environment factors between motor-vehicles and motorcycles. *Accident Analysis and Prevention,* 41, 938-947.

Long, J.S., 1997. "Regression models for categorical and limited dependentvariables." Thousand Oaks, CA, Sage Publications.

Majdzadeh, R., Khalagi, K., Naraghi, K., Motevalian, A., Eshraghian, M.R., 2008. Determinants of traffic injuries in drivers and motorcyclists involved in an accident. *Accident Analysis and Prevention,* 40, 17-23.

Pai, C.W., 2009. Motorcyclist injury severity in angle crashes at T-junctions: Identifying significant factors and analysing what made motorists fail to yield to motorcycles. *Safety Science,* 47, 1097-1106.

Pai,C.W., Hwang, K.P., Saleh, W., 2009. A mixed logit analysis of motorists' right-of-way violation in motorcycle accidents at priority T-junctions. *Accident Analysis and Prevention,* 41, 565-573.

Pai, C.-W., Saleh, W., 2007. Exploring motorcyclist injury severity resulting from various crash configurations at T-junctions in the UK –

an application of the ordered probit models. Traffic Injury Prevention 8 (1), 62–68.

Quddus, M.A., Noland, R.B., Chin H.C., 2002. An analysis of motorcycle injury and vehicle damage severity using ordered probit models. *Journal of Safety Research*, 33, 445-462.

Quddus MA, Wang C, Ison SG. 2009. The impact of road traffic congestion on crash severity using ordered response models, *Proceedings of the Transportation Research Board Annual Meeting*, Washington, D.C.

Rifaat, S.M., Tay.R., 2009a. Effect of Street Pattern on Injury Risks in Two-Vehicle Crashes. Transportation Research Record, No. 2102, pp. 61- 67.

Rifaat, S. M., Tay, R., Perez, A., De Barros, A., 2009b. Effects of Neighborhood Street Patterns on Traffic Collision Frequency. Journal of Transportation Safety and Security, Vol. 1, Issue 4, pp. 241- 253.

Rifaat, S. M., Tay, R., 2009c. Effect of Street Pattern on Single Vehicle Crash Severity. Proceedings of the 44th Annual Conference of Canadian Transportation Research Forum, Victoria, British Columbia, May 24- 27, pp. 180- 193.

Rifaat, S.M., Tay, R., 2008. Effect of Street Pattern on the Severity of Crashes Involving Vulnerable Road Users. Proceedings of the 18th Canadian Multidisciplinary Road Safety Conference, Whistler, BC, June 8-11, pp. 1- 15.

Rifaat, S.M., Chin, H.C., 2007. Accident Severity Analysis Using Ordered Probit Model. Journal of Advanced Transportation, Vol. 41, No.1, pp. 91-114.

Savolainen, P., Mannering, F., 2007. Probabilistic models of motorcyclists' injury severities in singleand multi-vehicle crashes. *Accident Analysis and Prevention, 39,* 955-963.

Shankar, V., Mannering, F., 1996. An exploratory multinomial logit analysis of single-vehicle motorcycle accident severity. *Journal of Safety Research*, 27(3), 183– 194.

Southworth, M., Ben-Joseph, E., 2003. Streets and the Shaping of Towns and Cities, Island Press, Washington DC.

Tay,R., Rifaat, S.M. (2007). Factors Contributing to the Severity of Intersection Crashes. Journal of Advanced Transportation, Vol. 41, No.3,pp.245-265.

Williams, R., 2006, "OGLM: Stata module to estimate Ordinal Generalized Linear Models." Available http://econpapers.repec.org/software/bocbocode/s453402.htm, accessed on 18th July 2008.

Williams, R., 2006a, "Generalized ordered logit/ partial proportional odds models for ordinal dependent variables." *The Stata Journal* 6(1):58-82.

Yannis, G., Golias, J., Papadimitriou, E., 2005. Driver age and vehicle engine size effects on fault and severity in young motorcyclists accidents. *Accident Analysis and Prevention*, 37, 327-333

Zambon, F., Hasselberg, M., 2006. Socioeconomic differences and motorcycle injuries: Age at risk and injury severity among young drivers: A Swedish nationwide cohort study. *Accident Analysis and Prevention*, 38, 1183-1189.