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APPLYING BAYESIAN HIERARCHICAL MODELS TO EXAMINE MOTORCYCLE CRASHES AT SIGNALIZED INTERSECTIONS

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ABSTRACT
Motorcycles are overrepresented in road traffic crashes and particularly vulnerable at signalized intersections. The objective of this study is to identify causal factors affecting the motorcycle crashes at both four-legged and T signalized intersections. Treating the data in time-series cross-section panels, this study explores different Hierarchical Poisson models and found that the model allowing *autoregressive lag 1 dependent* specification in the error term is the most suitable. Results show that the number of lanes at the four-legged signalized intersections significantly increases motorcycle crashes largely because of the higher exposure resulting from higher motorcycle accumulation at the stop line. Furthermore, the presence of a wide median and an uncontrolled left-turn lane at major roadways of four-legged intersections exacerbate this potential hazard. For T signalized intersections, the presence of exclusive right-turn lane at both major and minor roadways and an uncontrolled left-turn lane at major roadways of T intersections increases motorcycle crashes. Motorcycle crashes increase on high-speed roadways because they are more vulnerable and less likely to react in time during conflicts. The presence of red light cameras reduces motorcycle crashes significantly for both four-legged and T intersections. With the red-light camera, motorcycles are less exposed to conflicts because it is observed that they are more disciplined in queuing at the stop line and less likely to jump start at the start of green.

Keywords: Motorcycle crashes; Four-legged intersections; T intersections; Hierarchical models; Bayesian inference

1. INTRODUCTION

Motorcyclists have a poor safety record when compared with other road user groups. According to the Singapore Traffic Police annual statistics report for 2006 (Singapore Police Force, 2006), motorcycle crashes constitute about 36% of total road traffic crashes, even though their share in vehicle population is only about 18%. Moreover, motorcyclists account for almost 54% of road fatalities and about 51% of road injuries in the year 2006. Furthermore, the fatality and injury rates per registered vehicle among motorcyclists are respectively 13 and 7 times higher than that of other motor vehicles.

A substantial portion of motorcycle crashes in Singapore occur at intersections controlled by traffic signals. According to Traffic Police Annual Report 2006, motorcycles are involved in about 47% of crashes at Signalized intersections. Furthermore, while the crash involvement of motorcyclists as a victim of other road users is 43% nationwide, the corresponding percentage at signalized intersections is higher at 57%. These statistics signify that motorcyclists are more vulnerable at signalized intersections. Singapore crash statistics also show that motorcycles are involved in about 77% of fatal and about 67% of injury crashes that occurred at signalized intersections. Hence, it is worthwhile to study the intersection crashes of motorcycles to identify significant factors affecting the occurrence of such crashes.

1.1 Motorcycle Safety Research

There has been considerable research work on the motorcycle safety in the last two decades. A number of researchers (e.g., de Lapparent, 2006; Quddus et al., 2002; Shankar and Mannering, 1996) have attempted to quantify the effects of roadway, traffic, environmental, human and vehicle factors on motorcyclist injury severity while some other (e.g., Pai and Saleh, 2007; Pai and Saleh, 2008) have conducted the similar studies at intersections. A number of studies (e.g., Lin et al., 2003; Mannering and Grodsky, 1995; Rutter and Quine, 1996) have examined the crash risk based on the rider-motorcycle characteristics, while others (e.g., Williams and Hoffmann, 1979; Yuan, 2000) have examined the crash risk of motorcycles due to conspicuity related issues. These studies generally provide useful information on the crash risk and injury of motorcyclists. However, the road geometric and traffic related factors that may affect the occurrence of motorcycles crashes at signalized intersections have not been well explored.

The crash occurrence of motorcycles at signalized intersections is affected by their risk as well as their exposure. A number of studies (e.g., Hurt et al., 1981; Williams and Hoffmann, 1979) have reported that motorcyclists in the traffic stream are often overlooked by other drivers. This explains why the motorcyclists are overrepresented in right-of-way violation crashes in which vehicles from the conflicting stream encroach into the path of an approaching motorcycle (Clarke et al., 2007; Hurt et al., 1981). Moreover, drivers tend to over-estimate the motorcycle arrival times approaching to the intersection, hence increasing the possibility of a collision (Caird and Hancock, 1994).

On the other hand, the over-exposure of motorcycles at signalized intersections seems to increase their vulnerability to crashes. Haque et al. (2008) reported that motorcycles are over exposed at signalized intersections because they tend to accumulate near the stop-line during the red phase to facilitate an earlier discharge during the initial period of green. They have also showed that approaches with a wider lane width or with an exclusive right turn lane offer more freedom for motorcyclists to accumulate near the stop-line. Thus more exposed to the conflicting stream red light running vehicles.

Furthermore, the crash involvement characteristics of motorcycles are likely to different from other motor vehicles. Mannering and Grodsky (1995) have described several reasons why to differentiate the characteristics of the motorcycle crashes from those of other road user groups. Firstly, they claimed that "automobile drivers tend to be inattentive with regard to motorcyclists and have conditioned themselves to look only for other automobiles as possible collision of dangers". Secondly, the motorcycle riding is a complex task which requires excellent motor skills, physical coordination and balance. Motorcycle riding also requires counterintuitive tasks such as counter-steering, balanced application of front and rear wheel brakes and opening the throttle while negotiating turns.

A number of studies regarding traffic crashes at intersections have been mainly concerned with all vehicle crashes. Those have used frequency models which can model the number of crashes to the intersection related factors for examining the safety effects of such factors. For example, Chin and Quddus (2003) have examined traffic crashes at signalized intersections in Singapore; Vogt and Bared (1998) have conducted similar analysis at Minnesota and Washington; Poch and Mannering (1996) have examined intersection crashes at Bellevue, Washington. However, analyzing all intersection crashes together may not reflect the crash occurrence process and their influencing geometric and traffic related factors for a specific crash type or a specific road user group.

Realizing the importance of segregate analysis for a specific road user group or crash type, a number of researchers has also studied the crash occurrence process from this perspective. For example, Mitra et al. (2002) have studied intersection crashes by maneuver types; Abdel-Aty and Radwan (2000) have examined the arterial traffic crashes by segregating crashes by driver age and gender; Wang and Abel-Aty (2008) have modeled the left-turn crashes at signalized intersections by further separating conflicting patterns; Wang and Abdel-Aty (2006) have examined only rear end crashes at signalized intersections; Miaou (1994) has investigated the relationship between truck crashes and geometric design of road sections. However, the occurrence of motorcycle crashes at signalized intersections has not been well studied.

Moreover, motorcycles crash occurrences (as described earlier) at intersections may be different from other road user groups. Furthermore, intersection crashes could be more severe to the motorcyclists as injurious crashes such as angle collisions commonly take place at intersections (Pai and Saleh, 2007). Therefore, more extensive research on this area, especially motorcycle crashes at intersections, is highly justified.

1.2 Research Objective

The objective of this research is to explore the intersection-related factors on motorcycle crashes by establishing a more robust statistical relationship correlating motorcycle crash frequencies with intersection geometries and traffic characteristics at signalized intersections. The study examines four-legged and T signalized intersections separately.

2. METHODOLOGY

This section describes different statistical models considered for modeling motorcycle crashes at signalized intersections. The Bayesian inference which has been used for model calibration and assessment is briefly described and followed by the description of model selection criteria.

2.1 Model Development

Starting with the basic Poisson gamma model, several hierarchical models like Hierarchical Poisson Gamma, Hierarchical Poisson Lognormal, and Hierarchical Poisson Autoregressive lag-1 model have been explored to model motorcycle crash frequencies at signalized intersections. The framework and theoretical backgrounds of those models are presented here.

A significant number of traffic safety studies has been conducted to investigate the appropriateness of various count models that explore the relationship between geometric and traffic characteristics and the associated crash risk. The Poisson regression model is the basic count model which can describe discrete, random, non-negative and sporadic crash data. Since traffic crash data generally are over-dispersed, Poisson Gamma or Negative Binomial (NB) model has been developed from the Poisson model by introducing a stochastic component to relax the mean-variance equality constraint of the Poisson model (e.g., Miaou, 1994; Poch and Mannering, 1996; Lord, 2006).

Let, Y_{it} is the number of crashes at i^{th} entity and t^{th} time period is Poisson distributed and independents over all entities and time periods such as:

$$Y_{it} \mid \mu_{it} \sim Poisson(\mu_{it}) \qquad \text{i = 1, 2,……, I and t = 1, 2,.., T}$$

where μ_{it} is the crash mean for i^{th} entity and t^{th} time period.

Model 1: Poisson Gamma Model

The Poisson-Gamma or Negative Binomial model has been formulated to account for the over-dispersion in crash data by introducing a stochastic component to the mean of the standard Poisson model as follows (Lord, 2006):

$$\mu_{it} = \exp(\mathbf{X}'_{it}\boldsymbol{\beta} + \varepsilon_{it}) \tag{1}$$

where $\mathbf{X}_{it} = (1, X_{it,1}, ..., X_{it,k})'$ is a vector of covariates representing the site-specific attributes, $\boldsymbol{\beta} = (\beta_0, ..., \beta_k)'$ is a vector of unknown regression parameters, ε_{it} is the model error independent of all covariates. In the Poisson-Gamma model, it is assumed that $\exp(\varepsilon_{it})$ is gamma distributed ($Gamma \sim (\phi, \phi)$) with mean 1 and a variance $1/\phi$ for all i and t (with $\phi > 0$). The inverse dispersion parameter, ϕ allows accommodating extra variations of the crash data.

The over-dispersion can be caused by various factors, such as omitted variables, uncertainty in exposure and covariates, data clustering, unaccounted temporal correlation, model misspecification etc. In particular, the Poisson-Gamma model may not be appropriate for time-series cross-section panel data as data contain location specific effect and likely to be serially correlated. It is presupposed that distributions of crash occurrences for sites with similar observed characteristics are the same and crash counts for a specific location in different time periods are assumed to be independent with each other. Indeed, some unobserved features may necessarily exist between traffic sites and hence crash occurrences for a specific site may often be correlated serially. Consequently, without appropriately accounting for the location specific effects and potential serial correlations, the standard error estimations of regression coefficients may be underestimated and inferences from the estimated model may be misleading.

To explicitly model those structured heterogeneities introduced by data collection and clustering process, hierarchical or random effect models have been found to be better alternative in several recent traffic safety studies (e.g., Miranda-Moreno et al., 2007; Wang and Abdel-Aty, 2006; Chin and Quddus, 2003). These models can deal with the over dispersion problem due to unobserved heterogeneities as well as allow to incorporate the site-specific effects and complex variations, e.g., time and/or space patterns in the data. To introduce the hierarchical specification in the Poisson Gamma model the error term (ε_{it}) of the equation 1 can be replaced by a location specific random effect α_i. The gamma distribution assumption on $\exp(\alpha_i)$ leads to the Hierarchical Poisson Gamma specification as follows (Miranda-Moreno et al., 2007):

Model 2: Hierarchical Poisson Gamma Model

$$\begin{aligned} \mu_{it} &= \exp(\mathbf{X}'_{it}\boldsymbol{\beta} + \alpha_i) \\ \delta_i &= \exp(\alpha_i) \\ \delta_i &\sim Gamma(\varphi, \varphi) \end{aligned} \tag{2}$$

An alternative hierarchical specification may be the Hierarchical Poisson Lognormal Model which may be more suitable for modeling crash rates with a heavier-tailed distribution than the Gamma. The specification of this model is as follows:

Model 3: Hierarchical Poisson Lognormal Model

$$\begin{aligned} \mu_{it} &= \exp(\mathbf{X}'_{it}\boldsymbol{\beta} + \alpha_i) \\ \alpha_i &= \log(\delta_i) \mid \sigma_\alpha{}^2 \sim Normal(0, \sigma_\alpha{}^2) \end{aligned} \tag{3}$$

Hierarchical regression models here assume that the site-specific effects can explain the over-dispersion in the crash data. The random effect introduced by hierarchical models establishes that the effect of covariates on crashes at each site is the same but the intercept is different across the sites. Hence, the site-specific effect α_i induces a correlation among observations obtained at the same site. The underlying assumption is that the observations within an entity are exchangeable and hence the correlation is constant between any two observations within a site.

However observations in different time periods for a specific site may be serially correlated which means that disturbances associated with observations in one time period are dependent on disturbances from prior time periods. Serial correlations may exist in the crash dataset due to the effect of omitted variables, correlation over time, and a consequence of the nature of the phenomenon under study (Washington et al., 2003). In the context of this study, exogenous regressors in the longitudinal crash datasets seldom vary. Roadway geometrics and other design variables are practically constant with the exception of traffic volumes. Much of the dynamics in the longitudinal crash datasets arises from overlapping heterogeneity effects captured by the error term a "group of omitted variables" effect. If the omitted variables are correlated with the exogenous regressors, parameter bias is highly likely. Hence, treating serial correlations in the motorcycle crash count context would mitigate the potential for parameter bias.

Furthermore, the serial correlation may cause the estimated standard errors to be biased and hence may result in misleading inference on parameter estimates. Thus, an alternative specification may be the autoregressive lag 1 (AR-1) dependence specification in the errors to assess the possible autocorrelation. It weighs the correlation between two observations for a site by their separated gap (order of measure). As the periodical distance between observations within a site increases, the correlation decreases. The AR-1 model can be developed by adding a serial variation ω_{it} in the basic Poisson model which will allow modeling of lag-1 dependence in the errors (see Congdon, 2003 for detail). The specification of this model, with ρ as an autocorrelation coefficient, is given as follows:

Model 4: Hierarchical Poisson (AR-1) Model

$$\mu_{it} = \exp(\mathbf{X}'_{it}\boldsymbol{\beta} + \omega_{it}) \tag{4}$$
$$\omega_{i1} \sim Normal(0, {\sigma_{\omega}}^2 / (1-\rho^2))$$
$$\omega_{it} \sim Normal(\rho\omega_{i,t-1}, {\sigma_{\omega}}^2) \text{, for } t > 1 \text{ to T}$$

The aforementioned models can incorporate various structured heterogeneities in different way according to the specific type of crash data structures. Since the choice of one model over the other is not always clear, the appropriate model should be selected by comprehensive model diagnostics on the subject dataset. In this study, those above safety performance models will be employed to study the motorcycle crashes at signalized intersections and the suitable model will be selected from those based on the proper model selection criteria.

2.2 Bayesian Inference

Bayesian analysis is a process of fitting a probability model to the dataset and summarizing the posterior probability distribution on model parameters and on unobserved quantities. Instead of producing maximum likelihood estimates for unknowns totally based on the sample data, Bayesian methods explicitly use the probability for quantifying uncertainty in inferences based on the statistical data analysis. In Bayesian models, given model assumptions and parameters, the likelihood of the observed data is used to modify the prior beliefs of the unknowns, resulting in the updated knowledge in the form of posterior distributions (see Congdon, 2003 for detail).

Bayesian inference allows the flexibility in explicitly modeling hierarchical models. However, one of the common problems in the Bayesian hierarchical models is that the posterior distributions may not tractable algebraically in many cases, as the hierarchical models considered in this study. Moreover, posterior densities for the hierarchical models often lead to nonstandard densities. To overcome such analytical limitations, sampling-based estimation methods have been used. Markov Chain Monte-Carlo (MCMC) methods (Gilks et al., 1996) using Gibbs sampler and the

Metropolis-Hastings algorithm are widely applied to generate a large number of samples from posterior distributions. Any distribution summary (such as mean, median or quantiles) of the posterior distributions of model parameters or unknowns can then be approximated by their sample analogue.

2.3 Model Selection

Some commonly used model selection criteria are Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Deviance Information Criterion (DIC). A model assessment using the AIC or BIC requires the specification of the number of parameters in the model. However in complex hierarchical models whose parameters may outnumber the observations, these methods cannot be directly applied. Therefore for model evaluation, the Deviance Information Criterion (DIC), proposed by Spiegelhalter et al. (2003) is used. The DIC provides a Bayesian measure of model complexity and fit that can be used to compare models of arbitrary structure. Specifically, DIC is defined as:

$$DIC = D(\bar{\theta}) + 2P_D = \overline{D(\theta)} + P_D \tag{5}$$

where $D(\bar{\theta})$ is the deviance evaluated at the posterior means of estimated unknowns $(\bar{\theta})$, and $\overline{D(\theta)}$ is the posterior mean deviance that can be taken as a Bayesian measure of fit or "adequacy". P_D represents a complexity measure for the effective number of parameters in a model, as the difference between $\overline{D(\theta)}$ and $D(\bar{\theta})$, i.e., mean deviance minus the deviance of the means. As a generalization of AIC, DIC can thus been considered as a Bayesian measure of fit or adequacy, penalized by an additional complexity term P_D. As with AIC, models with lower DIC values are preferred.

While the DIC is used for the model selection, it is also necessary to justify whether the model fit the crash data well. In order to assess the fitness of the motorcycle crash data to the proposed models, the Predictive Loss Criteria, PLC (Gelfand and Ghosh, 1998) has been used. Let, Y_{it} be the observed data, ψ be the parameters, $\pi(\psi \mid y)$ be the posterior distribution, and Z_{it} be the predicted new data sampled from $f(Z \mid \psi)$ such as

$$f(Z \mid y) = \int f(Z \mid \psi)\pi(\psi \mid y)d\psi \tag{6}$$

Suppose, ξ_{it} and ς_{it} are the mean and variance of Z_{it}, then

$$PLC = \sum_{i=1}^{I}\sum_{t=1}^{T}\varsigma_{it} + [w/(w+1)]\sum_{i=1}^{I}\sum_{t=1}^{T}(\xi_{it} - Y_{it})^2 \tag{7}$$

where w is the weight factor. A Large value of w puts more weight on the match between the predicted and observed data. In this study, an infinite value for w is used to calculate the Predictive Loss Criteria.

2.4 Parameter Effects

In order to interpret the effect of explanatory variables included in the model, incidence rate ratios (IRR) have been computed for those variables. IRR provides an estimate of the impact of an explanatory variable on the expected crash frequency for one unit change in that variable. For observed crashes Y_{it} and a given set of explanatory variables $\mathbf{X}_{it}$, the expected number of crashes can be expressed as,

$$E(Y_{it} \mid \mathbf{X}_{it}, x_k) = \exp(\beta_0)\exp(\beta_1 x_1)......\exp(\beta_k x_k) \quad (8)$$

where, x_k is the variable of interest to calculate IRR. If x_k changes by one unit, then

$$E(Y_{it} \mid \mathbf{X}_{it}, x_k + 1) = \exp(\beta_0)\exp(\beta_1 x_1)......\exp(\beta_k x_k)\exp(\beta_k * 1) \quad (9)$$

Therefore, IRR for the variable x_k, the factor change in the expected crash count for a change of one unit in x_k, can be calculated as,

$$IRR = \frac{E(Y_{it} \mid \mathbf{X}_{it}, x_k + 1)}{E(Y_{it} \mid \mathbf{X}_{it}, x_k)} = \exp(\beta_k) \quad (10)$$

Hence, IRR for a variable is the exponential of its parameter estimate. The interpretation is that if IRR of a given variable is much less than 1.0 then an increase in value of the variable is associated with a significant reduction of motorcycle crashes (i.e., improvement on motorcycle safety). Conversely if IRR of an explanatory variable is much greater than 1.0, an increase in value of the variable results a significant decline on motorcycle safety. Otherwise, the variable has no effect on motorcycle safety (Olmstead, 2001; Chin and Quddus, 2003).

3. DATA PREPARATION

To establish an appropriate statistical model that examines the relationship between motorcycle crash frequencies and geometric and traffic characteristics, a total of 270 four-legged and 101 T signalized intersections from different parts of Singapore have been used. These account for about 19% of signalized intersections in Singapore and they are chosen because they have relatively high motorcycle activities. Note that Singapore is a city-state small island (700 km^2) country and fully urbanized.

In order to conduct the temporal analysis, the necessary data, including intersection geometric design features, traffic characteristics, and crash data for the same intersections, need to be collected over the study period. However, it is difficult to obtain all this information over a long period of time, and therefore data for the recent four years (2003 to 2006) have been used for the analysis. The intersection geometric features and traffic characteristics were provided by a consultancy company in Singapore.

Detailed records of motorcycles crashes at the selected sites were provided by the Singapore Traffic Police. A total of 1948 and 400 motorcycle crashes respectively at four-legged and T signalized intersections were recorded over that time period for those selected intersections. On an average each year respectively 1.80 and 0.99 motorcycle crashes have been found to occur at selected four-legged and T signalized intersections.

In crash frequency modeling on traffic crashes, data preparations have been conducted in several ways, i.e., approach level, roadway level or intersection level. For example, Poch and Mannering (1996) have fitted intersection crash frequency models at the approach level (i.e., four observations per intersection per year); Chin and Quddus (2003) have fitted an intersection traffic crash frequency model at the roadway level (i.e., two observations per intersection per year); Wang and Abdel-Aty (2006) have fitted crash frequencies at the intersection level (i.e., one observation per intersection per year). Wang and Abdel-Aty (2007) have investigated right-angle crashes at signalized intersections by modeling at the intersection, roadway, and approach levels. The data preparation for modeling by those different levels (intersection, roadway, or approach) has been elaborately discussed by Wang and Abdel-Aty (2007).

Analysis at approach and roadway level may better relate traffic crashes to characteristics of specific approach and/or roadway. However, such disaggregation of crashes may give rise to "site correlation" and cause excess zeros. To avoid excess zeros, Wang and Abdel-Aty (2007) might have aggregated the crashes over the study period of six years when modeling right-angle crashes at roadway and approach levels. However, such aggregation may not be able to account the temporal correlation of the crash data. Moreover, it may be difficult to assign traffic crashes of a particular vehicle group to any approach or roadway of an intersection if the exact point of collision is unknown and/or the fault assignment is complex. For simplicity as well as avoiding the problem of excess zeros, an intersection level crash analysis has been adopted in this study. Based on annual crash counts at 270 four-legged and 101 T signalized intersections over a four year period, a total of 1080 and 404 observations respectively have been obtained for model input for four-legged and T signalized intersections.

The roadway variables includes: (1) number of lanes, (2) presence of one way road, (3) presence of uncontrolled left-turn lane, (4) presence of exclusive right-turn lane, (5) presence of wide median, (6) presence of pedestrian crossing, (7) presence of red light camera, (8) speed limit, and (9) traffic volume. Those explanatory variables which represent the presence or absence of a geometric or traffic feature have been coded as dummy variables. It is worth mentioning that most intersection related variables are first inputted at the approach level. Since the intersection level analysis has been adopted, those approach level variables are aggregated into the roadway level (major and minor roadway). The roadways are defined as major and minor based on traffic volume. The explanatory variables of major and minor roadways for four-legged and T signalized intersections are shown in Table 1.

4. ESTIMATION OF RESULTS

This section illustrates the model calibration process and model diagnostic results for selecting the most appropriate model. The significant variables affecting motorcycle crashes at four-legged signalized intersections are explained and followed by the discussions of significant variables for T signalized intersections.

4.1 Model Estimation

The safety performance models are calibrated by the freeware software package WINBUGS 1.4 (Spiegelhalter et al., 2003) using the Markov Chain Monte Carlo (MCMC) algorithm (Gilks et al., 1996). The priors for regression coefficients $\boldsymbol{\beta}$ are assumed to have non-informative distributions such as Normal distribution (0, 1000). The hyper-parameters of the disturbance term of each of the models are also assigned a vague or non-informative prior. An inverse gamma distribution (0.001, 0.001) are assumed for $1/\phi, 1/\varphi$, σ_{α}^{2}, and σ_{ω}^{2} in the Poisson Gamma, Hierarchical Poisson Gamma, Hierarchical Poisson Lognormal, and Hierarchical Poisson (AR-1) model, respectively. All of the eight models, four models for each type of intersection, have been estimated by using three chains for MCMC up to 15,000 simulation iterations. The model convergence has been obtained after about 3000 iterations producing trace plots with a good degree of mixing and the convergence has been assured by the Gelman-Rubin statistics (Brooks and Gelman, 1998) below 1.2. After ensuring convergence, 5000 samples from each chain have been discarded as adaption and burn-in iterations. From rest samples, one in every tenth samples have been retained to reduce autocorrelation. This forms a total of 3000 samples for each of the parameter estimate.

Statistics of both model selection criteria, i.e., DIC and Predictive Loss Criteria, for all models are presented in Table 2. In all cases, the hierarchical models are found to be better than the standard Poisson Gamma model. This is expected as hierarchical structures exist extensively in the traffic crash data because of the data collection and clustering process. Among hierarchical models, the hierarchical Poisson Gamma and the hierarchical Poisson Lognormal are found to be competitive. For four-legged signalized intersections the Hierarchical Poisson (AR-1) model is found to be superior to other models based on both DIC with 3614.2 and PLC with 3912.3. For T intersections, though the Hierarchical Poisson (AR-1) model produces a slightly lower DIC (=928.2), the DIC values for all three hierarchical models have been found to be very similar (945.5 or 943.7). However, the Hierarchical Poisson (AR-1) model also shows an improved fit than other hierarchical models based on PLC (746.5 vs. 783.3 or 773.9). Hence, for both type of the intersections the Hierarchical Poisson (AR-1) model is found to be better than others. Moreover, the autocorrelation coefficient ρ, as shown in Table 3 and Table 4, is 0.567 and 0.916 for four-legged and T intersections respectively and both of them are also found to be significant. This further confirms that there exists strong structured temporal serial correlation effect in motorcycle crashes at signalized intersections and further justifies the appropriateness of this model.

Parameter estimates for motorcycle crashes by all candidate models for four-legged and T signalized intersections are presented in Table 3 and Table 4, respectively. To obtain the most parsimonious model, preliminary multicollinearity tests and backward stepwise method have been employed in selecting covariates. The insignificant variables have been dropped from the model one by one based on their significance level. The 95% Bayesian Credible Interval (BCI) have been used to interpret the significance of variables. Specifically, those coefficient estimations are significant whose 95% BCI do not cover zero. Furthermore, to interpret the effect of variables on the motorcycle safety, the Incidence Rate Ratio (IRR) has also been calculated. In Table 3 and Table 4, IRR of the explanatory variables have been reported only for the best fit model, i.e., Hierarchical Poisson (AR-1) model.

4.2 Interpretation of Significant Variables at Four-legged Intersections

An examination of Table 3 shows a number of factors to be significantly associated with motorcycle crashes at four-legged signalized intersections. For the major roadway, they are (1) number of lanes, (2) presence of uncontrolled left-turn lane, (3) presence of wide median, (4) presence of red light camera, (5) speed limit, (6) traffic volume. For the minor roadway, they are (1) number of lanes, (2) presence of red light camera, (3) traffic volume. The effects of these variables are discussed below.

4.2.1 Number of Lanes

The *number of lanes* along the major roadway of four-legged signalized intersections has been found to be significantly (95% BCI (0.01, 0.25), IRR 1.13) associated with motorcycle crashes. The IRR for this variable indicates that all other things being equal, a roadway with one additional lane increases the motorcycle crashes by about 13%. This may be because of several reasons. Firstly; a higher number of lanes allow more opportunities for motorcycles to move in between the traffic queue and accumulate in front of the stop line. This will increase the exposure of motorcyclists to the conflicting stream. Secondly; the number of the conflict points increases with the number of lanes. Thirdly; red light running propensity at intersections is higher on roads with higher number of lanes (Porter and England, 2000) and this is made worst because motorcycles are overexposed due to a higher likelihood of them forming up at the stop line (Haque et al., 2008).

For the minor roadway, the *number of lanes* has also been found to have a positive (95% BCI (0.001, 0.34), IRR 1.19) association with motorcycle crashes. The reasons are similar to those for the major roadway as discussed in the previous paragraph. Results show that an additional lane in the minor roadway increases the motorcycle crashes by about 19%. This higher value than the one for the major roadway is obvious as high number of lanes at the minor roadway is mainly for large intersections where the exposure problem of motorcyclists is likely to be higher.

4.2.2 Presence of Wide Median (>2 meter)

The *presence of wide median* in the major roadway of a four-legged signalized intersection is associated with higher motorcycle crashes (95% BCI (0.006, 0.44), IRR 1.20). Compared to roads without a wide median, roads with a wide median increase the motorcycle crashes by about 20%. There may be several reasons for the increase of motorcycle crashes due to the wide median. Firstly; a wide median often block the driver's views during the unprotected right-turn[1] green phase (Yan and Radwan, 2007). Moreover, the motorcycles approaching the junction are less likely to be perceived by the drivers compared to approaching cars (Crundall et al., 2008). Hence, less conspicuous motorcycles coupled with restricted driver's views in presence of a wide median are likely to increase the motorcycle crashes. Secondly; a wide median allows greater degree of spatial freedom for right-turning vehicles. Chin and Quddus (2003) have argued that wider median width may also create more conflicts between the interacting vehicles near the stop line as movements of through vehicles are less channelized. Thirdly; while crossing the intersection with a wide median, vehicles from the conflicting stream need a longer clearance time thus increasing the likelihood of crashes with motorcycles discharging early in the green (Haque et al., 2008).

Footnote: [1] In Singapore, driving is on the left side of the road

4.2.3 Presence of Uncontrolled Left-turn Lane

The *presence of uncontrolled left-turn lane* at the major roadway of an intersection is associated with higher motorcycle crashes (95% BCI (0.042, 0.40), IRR 1.23) and it increases such crashes by about 23%. The uncontrolled left-turn lane at signalized intersections allows left-turn vehicles to merge into the cross traffic stream. Chin and Quddus (2003) have reported that the presence of uncontrolled left-turn lane increases traffic crashes while Mitra et al. (2002) have reported that the presence of such lane increases head-to-side crashes. Hence motorcyclists may involve in head-to-side crashes for the traffic operations with the use of such a lane at signalized intersections. This type of crash involvement of motorcyclists may be due to several reasons. Firstly; motorcyclists tend to weave forward (Haque et al., 2008) and may queue to the left of the front vehicle, obvious that the driver may not know its presence while making the merge. Secondly; this queuing arrangement also makes the motorcycles invisible to the vehicles in the cross traffic. Thirdly; as suggested by Crundall et al. (2008), motorcycles from the cross traffic may be less perceived by drivers waiting for merging as motorcycles are less conspicuous. Fourthly; the arrival times of motorcycle from the cross traffic are likely to be misjudged by drivers (Caird and Hancock, 1994) waiting for merging and increase the possibility of collisions during merging.

4.2.4 Presence of Red Light Camera

The *presence of red light camera* (RLC) at the major roadway has been found to be effective in reducing motorcycle crashes (95% BCI (-0.66, -0.26), IRR 0.63). The corresponding reduction of motorcycle crashes is about 37% compared to roads without the RLC. Moreover, *the presence of red light camera*s at the minor roadway is also found to reduce motorcycle crashes (95% BCI (-0.54, -0.06), IRR 0.75) with the corresponding reduction of about 25%. Previous studies have shown that RLC is very effective in curbing red light violations (e.g., Chin 1989; Lum and Wong 2003) and hence potential right-angle crashes (Huang et al. 2006).

From a field study, Chin and Haque (in press) have reported that motorcycles are less disciplined in queuing behind the stop line where there is no red light camera (see Figure 1). They will discharge early in the green interval thus becoming more exposed to red-runners from the conflicting traffic stream. In the presence of a RLC, motorcyclists are reluctant to queue beyond the stop-line, so that there are fewer motorcycles in the front of the queue. Since weaving spaces become blocked by the motorcycles in front, the weaving opportunities for motorcyclists behind also reduce. Consequently, less motorcycle is discharging from the head of the queue as well as their start up is delayed due to waiting behind the stop line. Hence they are less exposed during the initial period of green which may reduce their not-at-fault crash involvements. Indeed, Haque et al. (2009) have reported that the presence of red light cameras reduce the not-at-fault crash involvement of motorcyclists. Hence RLC improves the safety to motorcyclists by not only reducing violations due to red light running but also motorcycle exposure due to a less accumulation in the front of the queue as well as a later start up.

The reduction of motorcycle crashes is higher when the RLC installs at the major roadway of four-legged intersections. This higher reduction is due to reduction in violations and exposure of motorcycles on the major road where the motorcycle traffic is likely to be higher than on the minor road.

4.2.5 Speed Limit ≥ 50 Km/h

Compared to roads with lower speed limits, higher-speed major roads are associated with the higher motorcycle crashes (95% BCI (0.27, 1.37), IRR 2.19). Previous studies, as reviewed by Aarts and van Schagen (2006), have also shown that roads with higher speed limits have the higher crash potential. Specifically, these roads may give rise to more rear-end crashes at the intersection (Poch and Mannering, 1996; Wang and Abdel-Aty, 2006). A rear-end collision at signalized intersections commonly happen when the leading vehicle chooses to stop at the onset of amber but the following vehicle decides to cross or fails to stop. Quddus et al. (2002) have argued that motorcyclists are less able to respond when the leading vehicle stops suddenly. This is worse on high-speed roads.

4.2.6 Traffic Volume

Traffic volume on the major roadway has been found to have a positive association (95% BCI (0.005, 0.051), IRR 1.024) with motorcycle crashes. Higher traffic on the minor roadway has also been found to show a positive effect (95% BCI (0.004, 0.030), IRR 1.015) on motorcycle crashes.

Exposure of crashes is likely to depend on the traffic volume. Available gaps for the right-turn opposing as well as the left-turn merging traffic are likely to reduce with the higher volume. Hence riders or drivers may more willing to take risk when making turn. Moreover, traffic volume has a significant correlation with the frequency red light running (Bonneson et al. 2001) in which motorcycles is particularly vulnerable.

4.3 Interpretation of Significant Variables at T Intersections

On T signalized intersections, (1) the presence of one way road, (2) presence of uncontrolled left-turn lane, (3) presence of exclusive right-turn lane, (4) presence of red light camera, (5) traffic volume at the major roadway and (1) the number of lanes, (2) presence of exclusive right-turn lane, (3) presence of red light camera, (4) speed limit of the minor roadway are found to be significantly associated with motorcycle crashes (See Table 4). The effects of those variables are discussed below.

4.3.1 Presence of One Way Road

Motorcycle crashes at T signalized intersections have been found to reduce significantly (95% BCI (-1.67, -0.22), IRR 0.40) if the major roadway is a one way road. The corresponding reduction of motorcycle crashes is about 60%. In a T configuration where only two movements per approach, the number of conflicting streams is greatly reduced when the major road way is a one way road. Specifically T intersections with one-way major road have only two conflicting groups while two-way major roads have five conflicting groups. Hence reduction of conflicting streams decreases motorcycle crashes significantly.

4.3.2 Presence of Uncontrolled Left-turn Lane

The *presence of the uncontrolled left-turn lane* on the major roadway is associated (95% BCI (0.01, 0.74), IRR 1.40) with the higher motorcycle crashes and it increases motorcycle crashes by about 40%. Generally, the provision of a left-turn lane creates more merging conflicts. In the T configuration, the uncontrolled left-turn at the major roadway allows vehicles to merge with right-turning vehicles from the oncoming traffic. This may result in a higher likelihood of a crash, perhaps sideswipe and head-to-side types which are more serious by nature. Moreover, with the difficulties to detect the motorcycles or to perceive correctly their speed, the likelihood of motorcycle crashes during merging by the uncontrolled left-turn lane will increase.

4.3.3 Presence of Exclusive Right-turn Lane

The *presence of exclusive right-turn lane*s in the major roadway has been found to increase (95% BCI (0.27, 1.58), IRR 2.50) motorcycle crashes by about 2.5 times over roads without exclusive right-turn lanes. Haque et al. (2008) reported that motorcyclists use the exclusive right-turn lane as a bypass if it is not fully utilized. In general, the utilization of the straight-through lanes and right-turn lanes are not balanced. Motorcyclists tend to utilize the unused lanes to maneuver to the front of the queue. Hence the presence of the right-turn lane gives more opportunity for motorcyclists to form up at the stop line, thus increasing the exposure to the traffic from the conflicting stream. Furthermore the vehicles in the exclusive right-turn lane may turn during the unprotected green phase making it hazardous to motorcyclists for several reasons: (1) right-turning drivers may not pay attention to motorcyclists around them (e.g., Hurt et al., 1981; Mannering and Grodsky, 1995), (2) turning drivers may be less able to perceive motorcycles from the opposing stream (Crundall et al., 2008), (3) drivers may over estimate the arrival time of motorcycles from the opposing stream (Caird and Hancock, 1994) and, (4) motorcycles are less conspicuous (e.g., Williams and Hoffmann, 1979).

The *presence of exclusive right-turn lane*s in the minor roadway has also been found to have a positive association (95% BCI (0.007, 0.99), IRR 1.60) with motorcycle crashes and the corresponding increase is about 60%. The right-turning vehicles from the minor roadway of a T intersection have potential conflicts with the through traffic from the major roadway. As right tuning vehicles from the minor roadway may take longer time to clear the T intersections, early discharging behavior of motorcyclists from the major roadway may increase the crash likelihood of motorcycles.

4.3.4 Presence of Red Light Camera

The *presence of red light camera* (RLC) along the major roadway also shows a decreasing effect on the motorcycle crashes (95% BCI (-1.27, -0.32), IRR 0.45) with a reduction of about 55% over the case of without a camera. The safety impact of RLC on motorcycle safety at T intersections is similar to that of four-legged intersections as discussed in the previous section.

4.3.5 Number of Lanes

Number of lanes on the minor roadway of T signalized intersections is found to have a positive association (95% BCI (0.01, 1.09), IRR 1.73) with motorcycles crashes. Lanes on the minor roadway of T configuration are used for either left turning or right turning. Hence turning lanes on the minor roadway of T signalized intersections appear to cause more motorcycle crashes. One additional lane on the minor roadway increases motorcycle crashes by about 73%. Higher number of lanes may increase two types of exposure. Firstly; weaving opportunities of motorcycles increase with higher number of lanes and thus accumulate in front of stop line and increase exposure of motorcyclists to the traffic from the major roadway. Secondly; the exposure of right-turning vehicles from major roadway increase with higher number of lanes at minor roadway as the crossing distance increases and hence lead to high number of crashes (Wang and Abdel-Aty, 2008).

4.3.6 Speed Limit ≥ 50 Km/h
The higher *speed limit* along the minor roadway is also found to have a positive association with motorcycle crashes (95% BCI (0.19, 2.49), IRR 3.57). Bonneson and Zimmerman (2004) have reported that the red-light violations increase for the roads with higher speed limit as the degree to which a driver underestimates his/her speed increases with speed. As motorcycles are highly exposed to the conflicting stream, high-speed roads with potentially higher red light violations are likely to increase the motorcycle crashes.

4.3.7 Traffic Volume
Motorcycle crashes have also been found to increase with the *traffic volume* (95% BCI (0.003, 0.015), IRR 1.008) on the major roadway of T intersections. Interactions between vehicles increase with the higher traffic volume and hence increase the likelihood of crashes. Moreover, higher traffic volume on major roadway will offer fewer available gaps for merging of left turning traffic from the minor roadway in case of operating priority controlled left turning and motorists may accept a smaller gap and hence higher risk.

Traffic volume on the minor roadway also shows a positive effect (95% BCI (0.002, 0.014), IRR 1.006) on the motorcycle crashes at T signalized intersections. The traffic from the minor roadway of T intersection is mainly turning vehicles. Hence increasing the volume of turning vehicles is likely to increase motorcycle crashes.

5. CONCLUSION
This study attempts to model the motorcycle crashes at four-legged and T signalized intersections in Singapore. The models have been employed to take care of unobserved heterogeneities as well as location-specific effects and/or serial correlations in the time of the crash counts. By treating the data in time-series cross-section panels, the Hierarchical Poisson (AR-1) model has been found to be superior in modeling motorcycle crashes at both four-legged and T signalized intersections. The further application of this model in hot spots or black spots identification may be promising.

Signalized intersections, being locations where there are many instances of speed differential between vehicles and conflicts between directional movements. While the severity of motorcycle problem may also be affected by the vulnerability of motorcycles, the study shows that there are a number of site-related factors which are linked to high motorcycle crash potential.

The presence of red light cameras reduces motorcycle crashes significantly for both four-legged and T intersections. It has been observed that the red light camera induces more disciplined queuing of motorcycles at the stop line hence reducing jump starts as well as less red-running on the conflicting approaches.

Higher imposed speed limits also affect motorcycle crashes at signalized intersections; increasing crashes for higher speed limit at major roadway of four-legged intersections but at minor roadway for T intersections. The presence of a wide median at major roadway of four-legged intersections has a positive association with high motorcycle crashes.

The number of lanes and presence of turning lanes have been found to affect motorcycle crashes for both types of intersections. The number of lanes is mainly found to have a significant influence on motorcycle crashes for four-legged intersections while the presence of turning lanes mainly influence crashes at T intersections. Four-legged intersections with more lanes at both major and minor roadways are linked to higher motorcycle crashes. However, higher number of lanes at minor roadways, i.e. turning lanes, of T signalized intersections is associated with higher motorcycle crashes. The presence of uncontrolled left-turn lane at the major roadway of both four-legged and T signalized intersections is associated with high motorcycle crashes. For T intersections, exclusive right-turn lanes on both major and minor roadways increase motorcycle crashes significantly. As a follow up to this study, further field work is now being carried out to understand the interactions between motorcycles and other vehicles operating during the turning phases.

Given these findings, more care should be exercised when designing intersections on high speed roads with multi-lanes and with exclusive right and left turn facilities, where a high proportion of motorcycles are expected in the traffic stream. One mitigating measure may be to install red light cameras on such sites.

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Table 1: Descriptive Statistics of Variables Included in Models for Four-legged and T Signalized Intersections

Variables	Four-legged Intersection				T Intersection			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Number of motorcycle crashes per year for intersection	1.804	1.690	0	10	0.990	1.270	0	7
Major Roadway								
Traffic Volume ADT in Thousand	18.431	4.285	5.70	37.52	15.489	4.599	4.80	30.27
Presence of One Way Road	0.104	0.305	0	1	0.099	0.299	0	1
Number of Lanes	4.222	0.800	2	6	3.624	0.688	2	5
Presence of Uncontrolled Left-turn Lane	0.722	0.448	0	1	0.554	0.498	0	1
Presence of Wide Median (>2m)	0.922	0.268	0	1	0.970	0.170	0	1
Presence of Exclusive Right-turn Lane[1]	0.930	0.256	0	1	0.881	0.324	0	1
Presence of Pedestrian Crossing	0.441	0.497	0	1	0.347	0.476	0	1
Presence of Red Light Camera	0.348	0.477	0	1	0.653	0.476	0	1
Speed Limit >= 50 Km/h	0.978	0.147	0	1	0.970	0.170	0	1
Minor Roadway								
Traffic Volume ADT in Thousand	14.509	4.549	2.85	31.27	10.447	3.438	2.55	25.01
Presence of One Way Road	0.119	0.323	0	1	0.079	0.270	0	1
Number of Lanes	3.330	0.865	1	5	2.168	0.599	1	4
Presence of Uncontrolled Left-turn Lane	0.770	0.421	0	1	0.574	0.495	0	1
Presence of Wide Median (>2m)	0.870	0.336	0	1	0.624	0.485	0	1
Presence of Exclusive Right-turn Lane	0.885	0.319	0	1	0.822	0.383	0	1
Presence of Pedestrian Crossing	0.422	0.494	0	1	0.366	0.482	0	1
Presence of Red Light Camera	0.163	0.370	0	1	0.119	0.324	0	1
Speed Limit >= 50 Km/h	0.938	0.167	0	1	0.911	0.285	0	1

[1] In Singapore, driving is on the left side of the road

Table 2: Model Comparison Criteria

Criteria	Intersection Type	Poisson Gamma	Hierarchical Poisson Gamma	Hierarchical Poisson Lognormal	Hierarchical Poisson (AR-1)
DIC	Four-legged	3711.21	3653.04	3654.07	3614.18
	T	992.94	945.51	943.67	928.18
PLC	Four-legged	4401.98	4322.46	4303.74	3912.27
	T	822.95	783.29	773.92	746.50

Table 3: Model estimates of significant variables for four-legged signalized intersections

Explanatory Variables	Poisson Gamma		Hierarchical Poisson Gamma		Hierarchical Poisson Lognormal		Hierarchical Poisson (AR-1)		
	Mean (SD)	95% BCI	Mean (SD)	95% BCI	Mean (SD)	95% BCI	Mean (SD)	95% BCI	IRR
Major Roadway									
Number of Lanes	0.126, (0.0544)	(0.014, 0.232)	0.135, (0.0635)	(0.013, 0.231)	0.122, (0.0625)	(0.011, 0.243)	0.125, (0.0624)	(0.012, 0.246)	1.133
Presence of Wide Median (>2m)	0.182, (0.1091)	(0.008, 0.414)	0.177, (0.1298)	(0.007, 0.437)	0.189, (0.131)	(0.005, 0.445)	0.184, (0.1299)	(0.006, 0.441)	1.202
Presence of Uncontrolled Left-turn Lane	0.214, (0.0922)	(0.042, 0.403)	0.205, (0.1060)	(0.038, 0.398)	0.199, (0.1063)	(0.036, 0.395)	0.210, (0.1059)	(0.042, 0.402)	1.234
Presence of Red Light Camera	-0.417, (0.0880)	(-0.588, -0.243)	-0.44, (0.1017)	(-0.642, -0.247)	-0.474, (0.1030)	(-0.680, -0.277)	-0.459, (0.1019)	(-0.661, -0.257)	0.632
Speed Limit >= 50 Km/h	0.782, (0.2452)	(0.324, 1.282)	0.778, (0.2763)	(0.257, 1.316)	0.779, (0.2762)	(0.253, 1.33)	0.786, (0.2767)	(0.272, 1.371)	2.195
Traffic Volume in ADT	0.027, (0.0125)	(0.003, 0.052)	0.027, (0.0146)	(0.007, 0.056)	0.025, (0.0147)	(0.006, 0.055)	0.023, (0.0142)	(0.005, 0.051)	1.024
Minor Roadway									
Number of Lanes	0.175, (0.0771)	(0.020, 0.321)	0.159, (0.0867)	(0.001, 0.331)	0.155, (0.0903)	(0.001, 0.332)	0.171, (0.0875)	(0.001, 0.340)	1.186
Presence of Red Light Camera	-0.278, (0.1043)	(-0.481, -0.071)	-0.285, (0.1187)	(-0.515, -0.051)	-0.307, (0.1210)	(-0.549, -0.067)	-0.294, (0.1210)	(-0.535, -0.060)	0.746
Traffic Volume in ADT	0.014, (0.0063)	(0.005, 0.025)	0.013, (0.0079)	(0.003, 0.276)	0.011, (0.0077)	(0.002, 0.026)	0.015, (0.0081)	(0.004, 0.030)	1.015
Intercept	-1.017, (0.3356)	(-1.68, -0.373)	-0.98, (0.3807)	(-1.72, -0.255)	-1.054, (0.3860)	(-1.818, -0.308)	-1.093, (0.3888)	(-1.848, -0.349)	
Variance[1]	0.219, (0.0355)	(0.151, 0.291)	0.138, (0.0262)	(0.09, 0.191)	0.139, (0.0263)	(0.093, 0.195)	0.152, (0.0393)	(0.079, 0.234)	
rho							0.567, (0.1070)	(0.354, 0.793)	
Number of Observations	1080		1080		1080		1080		

[1] $1/\phi$ for Poisson-Gamma, $1/\varphi$ for Hierarchical Poisson Gamma, σ_{α}^{2} for Hierarchical Poisson Lognormal, and σ_{ω}^{2} for Hierarchical Poisson (AR-1) model

Table 4: Model estimates of significant variables for T signalized intersections

Explanatory Variables	Poisson Gamma		Hierarchical Poisson Gamma		Hierarchical Poisson Lognormal		Hierarchical Poisson (AR-1)		
	Mean (SD)	**95% BCI**	**Mean (SD)**	**95% BCI**	**Mean (SD)**	**95% BCI**	**Mean (SD)**	**95% BCI**	**IRR**
Major Roadway									
Presence of One Way Road	-0.863, (0.2847)	(-1.465, -0.326)	-0.917, (0.357)	(-1.646, -0.222)	-0.903, (0.3642)	(-1.641, -0.203)	-0.914, (0.3687)	(-1.671, -0.219)	0.401
Presence of Uncontrolled Left-turn Lane	0.310, (0.1516)	(0.004, 0.608)	0.332, (0.2026)	(0.012, 0.732)	0.319, (0.2029)	(0.007, 0.733)	0.333, (0.2035)	(0.013, 0.735)	1.395
Presence of Exclusive Right-turn Lane	0.831, (0.2511)	(0.365, 1.360)	0.907, (0.3268)	(0.287, 1.557)	0.905, (0.3324)	(0.272, 1.587)	0.916, (0.3343)	(0.271, 1.578)	2.500
Presence of Red Light Camera	-0.599, (0.1663)	(-0.913, -0.278)	-0.707, (0.2307)	(-1.173, -0.276)	-0.833, (0.2408)	(-1.317, -0.376)	-0.794, (0.2422)	(-1.275, -0.323)	0.452
Traffic Volume in ADT	0.005, (0.0028)	(0.001, 0.012)	0.006, (0.0038)	(0.001, 0.013)	0.007, (0.0037)	(0.001, 0.014)	0.008, (0.0039)	(0.003, 0.015)	1.008
Minor Roadway									
Number of Lanes	0.510, (0.1946)	(0.118, 0.898)	0.557, (0.2709)	(0.022, 1.086)	0.508, (0.2688)	(0.013, 1.074)	0.548, (0.2776)	(0.005, 1.086)	1.729
Presence of Exclusive Right-turn Lane	0.421, (0.1826)	(0.059, 0.787)	0.533, (0.2501)	(0.043, 1.054)	0.458, (0.2428)	(0.03, 0.972)	0.473, (0.2583)	(0.007, 0.998)	1.604
Speed Limit >= 50 km/h	1.121, (0.4890)	(0.259, 2.166)	1.225, (0.5468)	(0.240, 2.423)	1.268, (0.5576)	(0.198, 2.556)	1.272, (0.5750)	(0.188, 2.490)	3.568
Traffic Volume in ADT	0.004, (0.0021)	(0.001, 0.009)	0.005, (0.0028)	(0.001, 0.012)	0.005, (0.0029)	(0.001, 0.011)	0.006, (0.0031)	(0.002, 0.014)	1.006
Intercept	-3.294, (0.6463)	(-4.64, -2.087)	-3.666, (0.8064)	(-5.315, -2.153)	-3.771, (0.8843)	(-5.603, -2.158)	-3.796, (0.8428)	(-5.574, -2.223)	
Variance[1]	0.254, (0.0966)	(0.076, 0.456)	0.359, (0.1022)	(0.193, 0.592)	0.387, (0.1123)	(0.210, 0.646)	0.06, (0.0438)	(0.005, 0.178)	
rho							0.916, (0.0627)	(0.759, 0.994)	
Number of Observations	404		404		404		404		

[1] $1/\phi$ for Poisson-Gamma, $1/\varphi$ for Hierarchical Poisson Gamma, σ_α^2 for Hierarchical Poisson Lognormal, and σ_ω^2 for Hierarchical Poisson (AR-1) model

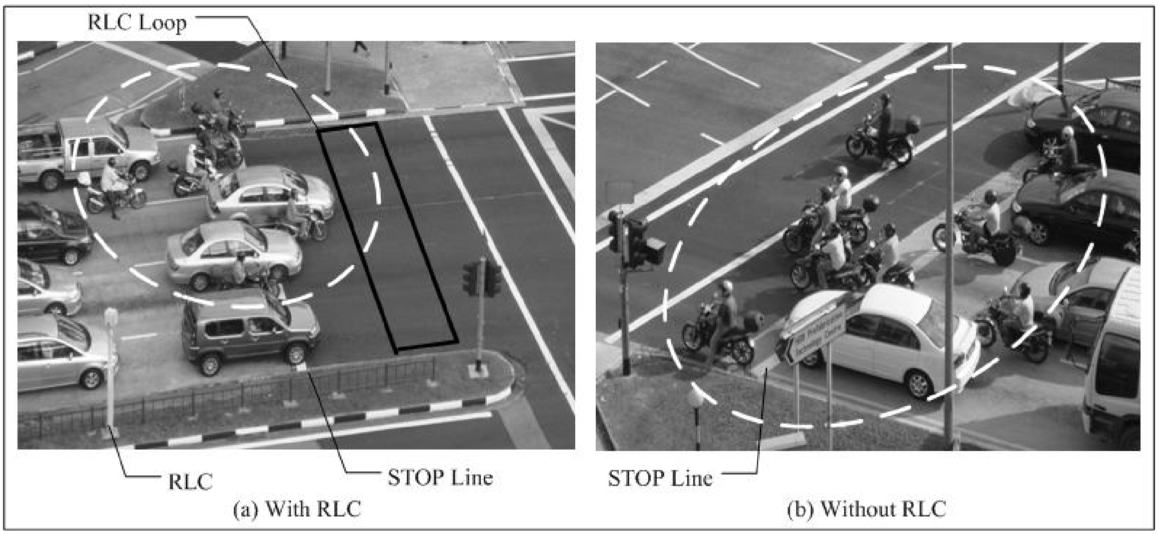

Figure 1: Effect of Red Light Cameras on the Queuing Pattern of Motorcyclists (Source: Chin and Haque, in press)