Impacts of Red-Light Cameras on Intersection Crash Frequency: A Hierarchical Spatial Model

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Enforcing red-light runners is known as an engineering solution to enhance the intersection safety. However, the efficiency of automated red-light camera (RLC) programs are always questioned mainly because of the inaccuracy in post-implementation reviews and difficulties with the financial viability of the program. An engineering analysis can address the concerns and improve the RLC programs. In this paper, we propose a methodology to capture the effect of RLCs on intersection safety by including the spatial dependency between intersections, unobserved heterogeneity, and the spillover effect of enforcing cameras. In this context, a Bayesian hierarchical model is implemented to spatially predict crash frequency at intersections. The safety impact of risk factors, such as land-use and intersection function, geometry and control characteristics, are examined. The proposed model was developed using 150 intersections located in the City of Chicago. The results show that the probability of crashes decreases at intersections equipped with enforcing camera by 6%. Also, the spillover effect of cameras is confirmed in this study by capturing the safety impact of cameras on other adjacent intersections. It is shown that crash risk is reduced by 2% for an intersection located within 1 km network distance from the RLC.

Keywords: Red-Light Camera, Spatial Correlation, Heterogeneity, Spillover Effect, Hierarchical Model
INTRODUCTION

Intersections safety is one of the most significant issues many cities face in managing traffic safety. It is shown that the red-light running (RLR) is a common cause of a crash at a signalized intersection (1). Red-light runners encompass about 800 death and 137,000 injuries annually in the US (2). Enforcement, as an effective way to change the driver’s behavior at intersections and consequently preventing RLR, incentivized cities to implement automated red-light camera (RLC) programs. In a study, the intersection's safety of 57 cities executing RLC program was compared to 33 cities that decided not to implement RLCs (3). The comparison showed that the ratio of RLR fatal crashes per capita to all intersection related fatal crashes improved by 21% after the implementation of a RLC program.

Despite the indisputable role of RLC on drivers’ behavior, RLC programs have always been under scrutiny. One common argument against the program is that RLCs exacerbate the intersection safety by referring to the increase in the number of crashes in some cities or in a given intersection after RLCs are installed. An evaluation of RLC in seven cities revealed that right-angle crashes were reduced by 25% while the rear-end crashes increased by 15% (4). Given that right-angle crashes are inherently high injury risk crashes comparing to rear-end collisions, the RLC program may still improve safety even if the total number of crashes increases. Also, the crash occurrence is dependent on many factors including the service volume of the intersection, local land use developments, etc., which needs to be considered before jumping into conclusion. This reveals the importance of engineering analysis of the RLC impact on traffic safety based on sufficient analyses of risk factors.

In addition, many RLC programs have been widely accused to be used to generate revenue for cities rather than being used for improving safety, given the fining regulations. However, the number of communities using the RLC has been dramatically decreasing since 2012 (from 533 to 430 communities according to the Insurance Institute of Highway Safety) because of difficulties in sustaining the financial viability of the program (2). Since the costs of the system are mainly attributed to the RLC operation costs, an efficient design would help to overcome the financial barriers in the RLC program. Patently, RLCs’ impact on crashes frequency needs to be captured thoroughly to help efficient allocation of the RLC.

In this study, we propose a methodological framework with the aims of capturing the effect of the RLC on crash frequency by: (1) taking observable factors (e.g. land use, intersection geometry and service volume) and unobservable spatial factors (e.g. immeasurable land use, social activities, and special events) that affect the crash frequency into account, (2) considering the unobserved heterogeneity at an intersection such as variation in drivers’ characteristics, and (3) investigating spatial effect of the RLC on other intersections’ safety.

LITERATURE REVIEW

The RLR role on intersection safety motivated researchers to investigate the factors that affect drivers’ behavior during the RLR violations (5-7). The impact of enforcement is mainly evaluated by associating the reduction in the RLR violations in presence of the RLC in an intersection (8-10). Various variables that have been examined can be summarized into the intersection control, geometry or functional characteristics. The red and yellow light duration and cycle length are features that can be used for reducing traffic violations (11-13). The number of approaches at the intersection, speed limit, right/left turn restriction and the number of lanes are the most significant variables that have been used in previous studies to characterize the intersection geometry (5; 14).
Also, the positive correlation between the intersection usage is confirmed in the form of volume-to-capacity of the average daily traffic (5; 8; 14).

From the methodological perspective, although the effectiveness of the RLC has mainly been investigated using before-after studies (e.g. (14-16)), a few studies have employed cross-sectional statistical models (e.g. linear, logistic, and generalized linear models) (5; 6; 8). The unobservable factors are generally ignored in these models. The fact remains, however, that the unobserved heterogeneity needs to be considered for unbiased parameter estimation, where the role of unobserved heterogeneity in crash frequency modeling context was extensively emphasized by Lord and Mannering, and Mannering and Bhat (17; 18). Ignoring the unobserved heterogeneity can result in inefficient and inconsistent parameter estimates (18). Spatial dependency can be driven from the unobserved similarity in interacted traffic flow as well as land-use and intersection characteristics (19). The spatial dependency in crash prediction models has been addressed in several studies using random parameters, spatial conditional autoregressive (CAR), and spatial weighting techniques (e.g. (20; 21)). Also, dealing with spatial correlation is considered as an instrument to boost the model prediction by econometricians (22). The effect of RLC on intersections located within the vicinity of an RLC (i.e. spatial spillover effect) has initially been discussed by Retting et al. in 1999 and then further examined by many researchers (23-25). Ahmed and Abdel-Aty in 2015 indicated that in addition to significant crash reduction at intersections equipped with an RLC, the other intersections’ safety improved in lesser magnitude but still significantly (25).

This paper contributes to the literature by filling the gap in previous studies. In this regard, we propose a Bayesian Spatial Hierarchical methodology framework capable of encountering the unobserved heterogeneity and the spatial dependency between intersections crashes. To evaluate the model, crash data collected at intersections located in the City of Chicago, which manages one of the biggest RLC programs in the US, are utilized. Since transportation safety can be manifested more clearly in analyzing injury crashes compared to RLR violations, the number of injury crashes is considered the dependent variable. A set of variables are examined as predictor which are grouped into intersection geometry, control, function, and land-use characteristics. Also, a spatially weighted predictor is defined to capture the spillover effect of RLCs. The model performance is evaluated by testing the model predicting power.

**METHODOLOGY**

A Bayesian Spatial Hierarchical Model is implemented in this study with three levels (26):

1) Data model: \[ \text{data} \mid \text{process, parameters} \],

2) Process model: \[ \text{process} \mid \text{parameters} \],

3) Parameter model: \[ \text{parameters} \].

In the first level, the data model describes the distribution of the observed crashes \( z \) given the true process \( \lambda(.) \). We assume crashes are independent conditional on \( \lambda(.) \), which is a valid assumption in crash measurement context. In other words, independence in the data model implies that the measurements of crashes frequency at intersections are independent. The data \( z = z(S) \) is observed at 150 points or observations (intersections), \( S = \{s_1, s_2, ..., s_{150}\} \). The data model then becomes: \[ z \mid \lambda(S) \].
The spatial dependence in crashes is modeled in the second level, the process model. The process model \( \lambda(.) \) conditional on the process parameters is assumed Gaussian stochastic process as:

\[
\lambda(.)|\beta, \theta_c \sim \text{GP}(\mu, C)
\]  

(1)

where \( \mu = x(s)'\beta, x(s) \) and \( \beta \) are vectors of predictors and coefficients. \( \theta_c \) is the parameter vector in respect to covariance function. \( C \) is covariance function such that \( \text{Cov}(\lambda(s_1), \lambda(s_2)) = \text{Cov}(\lambda(s_1) - \lambda(s_2)) \). We define the process with a spatially isotropic random field. This assumption implies that the mean is constant over space \( \mu(s) = \mu(s + h) \equiv \mu \), and the covariance function is only function of distance \( \text{Cov}(\lambda(s), \lambda(s + h)) = C(s, s + h) = C(|h|) \). Hence, the covariance function takes the form (26):

\[
C = \sigma^2 \rho(h)
\]  

(2)

where \( \sigma \) is the variance and \( \rho(h) \) is the correlation function as a function of \( h \). Two correlation functions, Matérn and Exponential, are utilized in this study. The Matérn and Exponential correlation function are specified as (26):

\[
\text{Matérn}: \rho(h) = \frac{\Gamma(v) (\frac{h}{\alpha})^\nu}{\Gamma(v)} K_v \left( \frac{h}{\alpha} \right), \quad \alpha > 0, \quad \nu > 0
\]  

(3)

\[
\text{Exponential}: \rho(h) = \exp\left( -\frac{h}{\alpha} \right), \quad \alpha > 0
\]  

(4)

where \( \alpha \) and \( \nu \) are parameters of the covariance function and estimate along with \( \sigma \) which construct the parameter vector \( \theta_c \). These parameters control the strength and scale of the spatial autocorrelation. The \( K_v \) is a modified Bessel function in second kind of order \( v \).

For parameter inference of Spatial Hierarchical Model, we need to integrate likelihood of data:

\[
L(\beta, \theta) = \int \text{Poission}(z) \text{N}(\lambda|\mu, C) \text{d}\lambda
\]  

(5)

Assuming the Poisson distribution of the data model and the Gaussian process of the process model, the likelihood function turns into the Eq. 6:

\[
L(\beta, \theta) = \int N(\lambda|\mu, C) \text{Poisson}(z|\lambda) \text{d}\lambda
\]  

(6)

The maximum likelihood estimate (MLE) of \( \beta \) and \( \theta \) are defined as the values that maximize the likelihood function \( L(\beta, \theta) \), or the log-likelihood \( \ell(\beta, \theta) = \log L(\beta, \theta) \). Based on the Bayesian thinking, the parameter distribution consists of the prior distribution for \( \beta \). So, the prior distribution is \( \beta \). In this case, the posterior is given by:

\[
[\beta, \theta|z] = \frac{[z|\beta, \theta|\beta]}{\int \theta [z|\beta, \theta|\beta] \text{d}\theta} \propto [z|\beta, \theta][\beta] = L(\beta, \theta)[\beta]
\]  

(7)

For this problem, the MLE is not available in a closed form and so is the posterior. In this case, numerical methods, such as the Markov Chain Monte Carlo (MCMC) simulation, are typically used for determining the posterior.. In this work, three goodness-of-fit measures, Mean Absolute Deviance, Mean-squared Predictive Error (MSPE), and Deviance Information Criteria (DIC) were used for assessing the model (Equations 8 to 10):

\[
MAD = \frac{1}{n} \sum_{i=1}^{n} |z_{estimate} - z_{observed}|
\]  

(8)
\[ MSPE = \frac{1}{n} \sum_{i=1}^{n} (z_{\text{estimate}} - z_{\text{observed}})^2 \]  

(9)

\[ DIC = \bar{D} + p_D = D(\theta) + 2p_D \]  

(10)

where is Equation 8 and 9, \( n \) is number of samples. In Equation 10, \( D \) is the average deviance, \( D(\theta) \) is the deviance of the posterior, and \( p_D \) is the effective number of parameters of the hierarchical model.

The Bayesian model enables us to account for the unobserved heterogeneity in observed crashes. Moreover, the spatial correlation is considered in the process model by defining the covariance function. The spillover effect can be examined by inferencing the presence of RLC as a variable in the process model.

EXPERIMENT

To verify the proposed method, we model intersection crash data from the City of Chicago. The city has one of the longest-running and largest RLC enforcement systems in the country and has been investigated in a few studies (14; 27). The cameras were initially installed between the years 2007 and 2010, and the RLC network has expanded since then. Since we are interested in the RLC for the periods 2005-2007 (before RLC installation) and 2010-2012 (after RLC installation) is modeled.

Data

In this study, four sets of data are used including; (1) crash data (all injuries: fatal, incapacitated, non-incapacitated, and possible) in two time periods, 2005-2007 and 2010-2012, (2) Chicago land-use spatial indicators, (3) RLC spatial indicators, and (4) the intersections function, control, and geometry characteristics. 150 intersections in Chicago are studied, where the cameras were active for 90 of them. The studied intersections are shown in Figure 1. The blue circles indicate the intersections without RLR enforcement, while the red circles represent intersections with an active RLC in 2010. Also, the distance matrix for spatial analysis which measures the network distance between intersections. The distance was extracted from the Google map API.
Crash Data

The crash dataset consists of the aggregated annual injury crash frequencies that occurred at intersections before and after installation of RLCs, both at signalized intersections with (90 sites) and without (60 sites) the presence of a camera. The preliminary analysis of the crash data shows that the average annual number of the crashes during the 2005-2007 was 12% higher than after installing the RLC (2010-2012). Respectively, the crash frequency, excluding rear-end crashes, dropped by about 24%. On the other hand, a (raw) 47% increase in rear-end crashes was observed after the RLC program (TABLE 1). Analyzing crashes at RLC equipped intersections before and after the program and comparing to the crashes from all intersections indicates a positive effect of RLC at intersections with the camera (for all crashes, except rear-end). Also, the distribution of the injury crashes represents the change in crashes frequency in each intersection (FIGURE 2).

FIGURE 1. The RLR Enforcement at Chicago Intersections in 2010.
Table 1. Number of Injury Crashes at Chicago Intersections Before and After the RLC Program

<table>
<thead>
<tr>
<th>Intersection Type</th>
<th>Crash type (annual)</th>
<th>Number of Crashes</th>
<th>Before Installing Camera</th>
<th>After Installing Camera</th>
<th>Change (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Intersection in Chicago</td>
<td>Total Crashes</td>
<td>1777</td>
<td>1557</td>
<td>-12.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total Crashes Excluding Rear-End</td>
<td>1496</td>
<td>1142</td>
<td>-23.7</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rear-End Crashes</td>
<td>281</td>
<td>415</td>
<td>47.7</td>
<td></td>
</tr>
<tr>
<td>Intersections in RLC Program</td>
<td>Total Crashes</td>
<td>1228</td>
<td>1063</td>
<td>-13.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total Crashes Excluding Rear-End</td>
<td>1038</td>
<td>767</td>
<td>-26.1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rear-End Crashes</td>
<td>190</td>
<td>296</td>
<td>55.8</td>
<td></td>
</tr>
</tbody>
</table>

FIGURE 2 Average Annual Injury Crash Distribution at Chicago Intersections Before and After the RLC Program

Notwithstanding the encouraging result of crash frequency analysis, crashes need to be studied in more details. FIGURE 2 shows the ratio of all types of crashes (all severities) over Annual Daily Traffic (ADT) at intersections. From the figure, it is apparent that the spatial dependency in crashes exists at Chicago intersections.

Land-Use

The role of land-use on drivers’ behavior incentivized the authors to attempt to account for the land-use characteristics. Particularly, it is shown that the drivers take more risk while driving under the influence which can cause red-light running (28; 29). We tested this hypothesis by
examining the effect of land-use activities which serve alcohol on intersections crash frequency. To this extent, the major points of interests (POIs) in Chicago are collected using the Open Street Map POI dataset and corresponding variables are created in form of the POIs density in 500, 700 and 1000 meters buffer around the intersection. The distribution of bars and restaurants is illustrated in FIGURE 3 (note: the data do not include all establishments that serve alcohol. Nonetheless, we still use this variable as part of the modeling effort).

FIGURE 3 (a) Injury Crashes per 10000 ADT Distribution at Chicago Intersections Before Installing RLC, and (b) Injury Crashes per 10000 ADT Distribution at Chicago Intersections After Installing RLC

To be able to examine the spillover effect of RLCs, spatial indicators were produced. In this context, the distance matrix of Chicago intersections was extracted from the Google API service. In addition to testing the linear spillover effect of RLCs, the presence of a camera at the intersection is spatially weighted in form of, inverse spatial weighted and squared inverse spatial weighted.

Intersection Characteristics
While the intersection characteristic impacts on crashes are broadly illustrated in the literature,
various variables were analyzed to measure this effect. The intersection function was defined in
term of the annual traffic passing through the intersection and speed limit. It is expected that more
Crashes occur at an intersection with higher service volume. The right and left turn by drivers can
cause angled crashes which have a destructive impact on intersection safety. In this regard, the
possibility of right turn on red and the availability of left lanes in the intersection were evaluated.
The number of lanes and the median type of the approaching intersections can be a helpful
representative of the way intersection influence the drivers’ behavior. Table 1 summarizes key
variable statistics.
Table 1 Summary of Intersections Characteristics

<table>
<thead>
<tr>
<th>Street Type</th>
<th>Variable</th>
<th>Statistic/Condition</th>
<th>With RLC (90 sites)</th>
<th>Without RLC (60 sites)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average AADT [2005-2007] (veh/day)</td>
<td>Minimum</td>
<td>7,000</td>
<td>10,100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum</td>
<td>55,500</td>
<td>61,000</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>24,200</td>
<td>22,809</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Std. dev</td>
<td>9,243</td>
<td>9,526</td>
</tr>
<tr>
<td></td>
<td>Average AADT [2010-2012] (veh per day)</td>
<td>Minimum</td>
<td>5,625</td>
<td>10,000</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum</td>
<td>58,750</td>
<td>56,800</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>23,154</td>
<td>21,587</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Std. dev</td>
<td>9,463</td>
<td>8,693</td>
</tr>
<tr>
<td>Major</td>
<td>Number of Lanes</td>
<td>Minimum</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum</td>
<td>8</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>3.6</td>
<td>3.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Std. dev</td>
<td>1.1</td>
<td>1.2</td>
</tr>
<tr>
<td></td>
<td>Right-Turn-on-Red (proportion of intersections)</td>
<td>Prohibited Limited</td>
<td>9%</td>
<td>8.50%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Allowed</td>
<td>18%</td>
<td>20.50%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Not-controlled</td>
<td>73%</td>
<td>71.00%</td>
</tr>
<tr>
<td></td>
<td>Left Turn Lane (proportion of intersections)</td>
<td>Not Present</td>
<td>8%</td>
<td>15%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Present</td>
<td>92%</td>
<td>85%</td>
</tr>
<tr>
<td></td>
<td>Posted Speed Limit (miles per hr)</td>
<td>Minimum</td>
<td>20</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum</td>
<td>35</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>29.9</td>
<td>30.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Std. dev</td>
<td>2.1</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>Not Present</td>
<td>67%</td>
<td>71%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Present</td>
<td>33%</td>
<td>29%</td>
</tr>
<tr>
<td>Minor</td>
<td>Number of Lanes</td>
<td>Minimum</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Maximum</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>2.6</td>
<td>2.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Std. dev</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Right-Turn-on-Red (proportion of intersections)</td>
<td>Prohibited</td>
<td>10%</td>
<td>12%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Limited Allowed</td>
<td>19%</td>
<td>19%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Not-controlled</td>
<td>71%</td>
<td>69%</td>
</tr>
<tr>
<td></td>
<td>Left Turn Lane (proportion of intersections)</td>
<td>Not Present</td>
<td>13%</td>
<td>15%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Present</td>
<td>87%</td>
<td>85%</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>Not Present</td>
<td>90%</td>
<td>96%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Present</td>
<td>10%</td>
<td>4%</td>
</tr>
</tbody>
</table>
Model and Discussion

Using the method discussed above, a model fitting the annual number of injury crashes to the covariates can be estimated. The data model \((z)\) is assumed to be a Poisson distribution with a Gaussian process. The dataset was constructed as panel data and split into two sets for modeling purposes. The Test and Training Set were sampled randomly, where the test and training dataset contained 10% and 90% of the intersections, respectively. The model was initially estimated using the Training Set, and the Test Set was used to evaluate the model performance. A binary variable was used to indicate the presence of an RLC at signalized intersections. The relationship between traffic flow and crashes followed a non-linear pattern, which is commonly used for highway safety models. The parameter estimation has been done using basic MCMC simulation in R \((30)\). The samples are obtained by the Gibbs sampler algorithm. The first 10,000 iterations were considered for the burn-in period and the parameters were estimated based on 20,000 iterations.

TABLE 3 summarizes the modeling results. The estimators are statistically significant with 10% posterior significant levels. The term \(\alpha\) represents the decay rate of the exponential correlation function. According to the value of the exponential correlation function parameter \((\alpha)\), the spatial dependency between intersections dissipates within 3 kilometers (approximately). As expected, the coefficient of intersections traffic is positive which implies that the more vehicles pass through the intersection, the more crashes will occur, although at a decreasing rate. A 1% increase in traffic in each lane is associated with a 0.5% increase in the probability of a crash. The results show that the more lanes that are linked to the intersection, the higher the probability of a crash. According to the model, the presence of median in the minor approach improves the intersection safety by 8%. The effectiveness of RLC is shown by capturing a 6% lesser chance of crash for intersections equipped with a camera, which supports a recent study that used the same data \((14)\). Not only RLCs improve intersection safety but also reduces the probability of a crash by 2% within a 1 km radius. Respectively, the presence of enforcing cameras with a 2-km distance could reduce the crash occurrence probability by 1%. The land-use characteristics which have been examined in form of the alcohol-serving POI density in 500, 700 and 1000 meters buffer within, are correlated with the intersection ADT. Consequently, the variables with dominant effect on crashes (intersection ADT) was used.

**TABLE 3. Modeling Results**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimate (Posterior Standard Deviation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-3.12 (0.77)</td>
</tr>
<tr>
<td>Log of the average daily traffic in each lane</td>
<td>0.51 * (0.14)</td>
</tr>
<tr>
<td>Number of lanes linked the intersection</td>
<td>0.02 * (0.00)</td>
</tr>
<tr>
<td>Median presence in minor approach</td>
<td>-0.08 *** (0.03)</td>
</tr>
<tr>
<td>RLC presence</td>
<td>-0.06 ** (0.02)</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Inverse distance of RLC to intersection</th>
<th>-0.02 **</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1/km)</td>
<td>(0.00)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Goodness-of-Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAD</td>
</tr>
<tr>
<td>MPSE</td>
</tr>
<tr>
<td>DIC</td>
</tr>
</tbody>
</table>

Asterisks *, **, and *** correspond with statistical significance levels at the 5%, 10%, and 15%, respectively.

To verify the model performance, the prediction power of the model was assessed by comparing the predicted and observed crash frequency with the test dataset. The absolute error of prediction is defined as the difference between the predicted and observed number of crashes. In FIGURE 4, the absolute prediction error spatial distribution is depicted and compared with the observed crashes in training set. As is shown in this figure, the error magnitude is correlated with the observed point density. The more observations at an intersection’s neighbor are, the higher accuracy in prediction will be. Also, as is seen in FIGURE 5, the histogram of the absolute prediction errors shows that for 50% of intersections, the crashes are estimated with 1 margin of error.

Figure 4. The Spatial Distribution of Absolute Prediction Error
SUMMARY AND CONCLUSIONS
Red-light running at signalized intersections is an important safety problem for many cities. Although a lot of studies have been performed for assessing the safety effects of red-light cameras, most of the studies have focused on using a before-after study framework. These studies do not take into account spatial correlation and land-use characteristics that could influence crash risk. In this paper, a Bayesian hierarchical model was developed for evaluating the RLC effect on injury crashes. The proposed model provides the capability of encountering unobserved heterogeneity in crashes and spatial dependency between intersections as well as capturing the spillover effect of RLC in the network. The model was developed using data collected at Chicago intersections. Among the various land-use and intersection characteristics, crash frequency was associated with the traffic passing through the intersection, the size of the intersection in terms of the number of approach lanes, the presence of a divided median on the minor approach and the red-light enforcement at the intersection. The results shed further lights on the improving impact of RLCs on intersection safety by reducing the chance of an injury crash by 6% (all collision types). In addition, 2% fewer crashes are expected at intersections within 1 km network distance to the RLC location. From the practical standpoint, using the proposed model for analyzing the RLC performance can result in a reliable assessment of the program. Also, results of this study can help previous attempts to investigate the economic feasibility of RLC programs and the allocation of RLCs in the network to achieve the highest efficiency (13; 31). Finally, further work includes the examination of intersections that experienced more than 4 crashes per year prior to the installation of the camera as well as separating crashes by collision type; recent work have shown that cameras installed at such intersections were more efficient (14).

CONTRIBUTION
The authors confirm contribution to the paper as follows: study conception and design: Soheil Sohrabi; data collection: Dominique Lord; analysis and interpretation of results: Soheil Sohrabi;

Figure 5. Absolute Prediction Error Distribution
References


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