Safety Effects of the Red-Light Camera Enforcement Program in Chicago, Illinois

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ABSTRACT

The objective of this study aimed at evaluating the safety effects of the red-light camera (RLC) enforcement program in Chicago, Illinois. The work was conducted on behalf of the Chicago Tribune, which collected and assembled data at 4-legged signalized intersections where one or more RLCs were put in operation in 2008 or 2009. Crash, geometric and traffic flow data were collected at 90 sites for three years before and for three years after the installation of the cameras as well as at 59 sites where no camera was installed to capture time-related changes that occurred within the Chicago area. To accomplish the study objective, an empirical Bayes (EB) analysis was employed for evaluating the safety effects of the RLC program. The study results show that a non-significant increase of 5% in the total number of injury crashes, a statistically significant reduction of 15% in angle and turning injury crashes, and a statistically significant increase of 22% in rear-end injury collisions were noted. Based on the study results, it is also hypothesized that driver behavior may have been affected at signalized intersections where no RLC was utilized.

1.0 INTRODUCTION

This research report documents the steps taken to evaluate the safety effects of the red-light camera (RLC) enforcement program in Chicago, Illinois. The work was conducted on behalf of the Chicago Tribune, which collected and assembled crash, geometric and traffic flow data at signalized intersections where one or more RLCs were put in operation in 2008 or 2009. For this study, data collected from 90 sites before and after the installation of the cameras were used. These 90 sites will be referred to as the "treatment group" further below. Both study periods covered three years: 2005-2007 for the before period and 2010-2012 for the after period. Data collected at 59 sites where no camera was installed in order to capture time-related changes that occurred within the Chicago area were also used. The same time periods as for the treatment group were utilized. These sites will be referred to as the "reference group" subsequently in the text. The Chicago Tribune assumed full responsibility for the quality of the data collected at these sites. Although the researchers did not participate in the data collection process, the exploratory analyses of the data showed the data to be of good quality.

Three types of analyses were conducted: 1) Simple before-after or Naïve method, 2) the before-after study with reference group; and, 3) the empirical Bayes (EB) method. The characteristics of these types of studies as well as the results of these analyses are presented below. Overall, the study results show that, based on the naïve estimate, a 9% reduction in the total number of injury crashes, a 41% percent reduction in angle and turning injury crashes, and a 61% increase in rear-end injury collisions were observed at the 90 signalized 4-legged intersections. However, when the reference group is included in the analysis and the EB method is used for estimating the effects of the enforcement program on safety, a non-significant increase of 5% in the total number of injury crashes, a statistically significant reduction of 15% in angle and turning injury crashes, and a statistically significant increase of 22% in rear-end collisions were noted. Based on the study results, it is also hypothesized that driver behavior may have been affected at signalized intersections where red-light cameras were not used.

This report is divided into four sections. Section 2.0 describes the key features of the methodology used for analyzing the safety effects. Section 3.0 shows the summary statistics of the data collected by the Chicago Tribune. Section 4.0 documents the results of the before-after analyses. The last section provides a summary and discussion about the key results of this study.

2.0 METHODOLOGY

This section is divided into two subsections. The first subsection describes the definitions used for the various analyses described below. The second subsection presents the characteristics of the simple before-after study, the before-after study with reference group, and the EB method.

2.1 DEFINITIONS

Independent of the method used, before-after studies are usually accomplished using two tasks (Hauer, 1997):

Task 1: Predict what would have been the safety of a site in the after period, had the treatment not been implemented.

Task 2: Estimate the safety of the treatment at the site after implementation.

For accomplishing these two tasks, the following terms need to be explained:

- The variable π is defined as the expected number of crashes at a specific site in the after period if the treatment has not been implemented. This variable only applies for the targeted crashes (i.e., total, rear-end, right-angle, etc.) and/or their severity (i.e., fatal, incapacitating injury, property damage only, etc.). π is referred to as the 'predicted value'.

- The variable λ is used to define the expected number of crashes in the after period (after the implementation of the treatment). λ is referred to as the 'estimated value'.

The effects of a treatment are estimated by comparing both variables above in the following manner:

- The reduction (or increase) in the expected number of crashes is given as $\delta = \pi - \lambda$. A positive number indicates a decrease in the expected number of crashes.

- The ratio or the Index of Safety Effectiveness is defined as $\theta = \lambda / \pi$. If the number of crashes analyzed is below 500 for the before period, θ needs to be adjusted by the following factor: $1 + Var\{\pi\} / \pi^2$. This adjustment is used to minimize the bias caused by a small sample size. The Index of Safety

Effectiveness therefore becomes the following: $\theta = \frac{\lambda/\pi}{\left[1+Var\{\pi\}/\pi^2\right]}$. A value below 1.0 indicates a reduction in the number of crashes.

The variable $Var\{\pi\}$ is referred to as the variance of π, while the variable $Var\{\lambda\}$ is referred to as the variance λ. The variance is a measure of uncertainty associated with the estimated value.

The variance of the reduction, δ, is calculated as follows:

$$Var\{\delta\} = Var\{\pi\} + Var\{\lambda\} \tag{1}$$

The variance of the Index of Safety Effectiveness is equal to

$$Var\{\theta\} = \theta^2 \left[\frac{\left(Var\{\lambda\}/\lambda^2\right) + \left(Var\{\pi\}/\pi^2\right)}{\left(1+Var\{\pi\}/\pi^2\right)^2} \right] \tag{2}$$

Table 1 lists the variables used when a reference group is utilized. The Latin characters represent the number of crashes that occurred at the sites under study. The Greek letters represent the expected or estimated number of crashes at those sites. How these variables are used is described below.

Table 1. Observed and Expected number of Crashes

	Treatment Group	**Reference Group**
Before	K, κ	M, μ
After	L, λ	N, ν

The safety effectiveness of an intervention is estimated using a 4-step process (Hauer, 1997):

Step 1: Estimate λ and π.

Step 2: Calculate the variance of λ and π. As discussed above, they are defined as $Var\{\lambda\}$ and $Var\{\pi\}$, respectively.

Step 3: Estimate the difference δ and the Index θ.

Step 4: Calculate the variance of δ and θ. They are defined as $Var\{\delta\}$ and $Var\{\theta\}$, respectively.

The steps above are done for each site individually and the estimated and predicted values, as well as their variances, are summed for all the sites that are analyzed simultaneously. Additional discussion on this topic is presented in the EB method below.

The next three subsections present the characteristics of the three methods used for this study.

2.2 NAÏVE BEFORE-AFTER STUDY

The naïve before-after study is the simplest method among the ones used for evaluating the safety effects of interventions (Hauer, 1997). The goal of this method is to collect crash data that occurred during the before period and use them as the predicted value for the after period (π). With this method, the number of crashes can be adjusted for the differences in traffic flow and the length of the study period before and after the implementation of the treatment(s). Equation (3) shows how the predicted value can be adjusted as a function of traffic flow and time periods (Hauer, 1997):

$$\hat{\pi} = r_d r_{tf} \hat{\kappa} \tag{3}$$

where,

$\hat{\pi} =$ the predicted number of crashes for the after period,

$r_d = \dfrac{\text{Duration of the after period}}{\text{Duration of the before period}}$ or the ratio between the after and before periods,

$r_{tf} = \dfrac{\text{Traffic flow during the after period}}{\text{Traffic flow during the before period}}$ or the ratio in traffic flow between the after and before periods,

$\hat{\kappa} =$ the estimated number of crashes during the before period (in this case, $\kappa = K$, the number of crashes in the before period)

The ratio r_{tf} can be linear or non-linear, r_{tf}^{β}, depending on the characteristics of the data. Usually, β has been shown to vary between 0.5 and 1.0 (the latter representing a linear relationship). The "^" in Equation (3) and all subsequent equations refer to an estimate of a variable.

The variances for the naïve method are defined as follows:

$$Var(\hat{\pi}) = r_d^2\hat{\kappa} \quad (4)$$

$$Var(\hat{\lambda}) = L \quad (5)$$

In Equation (4), the uncertainty associated with r_{tf} was not included in the calculation of the variance for π, since the coefficient of variation of the traffic flow is not known. The variance for λ is equal to the number of crashes in the after period, with the assumption that the crash count follows a Poisson distribution over the entire study time period.

The advantages of the naïve method are as follows:

- The data collection is simplified since it is performed only at the treated sites.
- This method can account for changes in traffic flow and time periods.

For the disadvantages, we find the following:

- Does not account for local and regional changes, such as weather patterns and economic conditions.
- Does not account for the regression-to-the-mean (RTM) and site selection effects. The RTM dictates that sites characterized with a large (or small) number of observations in the before period are expected to observe a smaller (or larger) number of observations in the after period, closer to the long-term average or mean of the site, if nothing changes. Site selection effects refer to sites where an entry criterion is used to be selected for further analyses (i.e., four crashes per year, etc.). Although both biases are related, they are in fact different (Davis, 2000; Cook and Wei, 2002; Lord and Kuo, 2012).

Because of its simplicity and the smaller resources to collect data, this method is the most widely used among transportation agencies.

2.3 BEFORE-AFTER STUDY WITH REFERENCE GROUP

This method uses the same approach as the naïve method, but utilizes a reference group in order to capture local and regional changes, as discussed above (Hauer, 1997). Equation (6) adds the term r_{rg}, but removes the term r_d, to Equation (3):

$$\hat{\pi} = r_{tf} r_{rg} \hat{\kappa} \quad (6)$$

where,

$r_{rg} = \frac{\nu}{\mu}$ with the assumption that $r_{rg} = r_t = \frac{\pi}{\kappa}$, which is the ratio in estimated number of crashes between the before and after periods for the reference group and this ratio is considered the same as for the treatment group. The duration for the treatment and reference groups need to be identical as well (so that r_d is captured by r_{rg}).

The variances for the before-after study with reference group method are defined as follows:

$$Var\{\hat{\pi}\} = \hat{\pi}^2 \left[1/K + 1/M + 1/N + Var\{\hat{\omega}\}\right] \tag{7}$$

$$Var\left(\hat{\lambda}\right) = L \tag{8}$$

In Equation (7), the uncertainty associated with r_{tf} was not included in the calculation of the variance for π, similar to the naïve method. In this equation, $Var(\omega)$ is assumed to be equal to 0.001. Equation (8) is the same as Equation (5).

Although the reference group method is superior to the naïve method, it still does not account for the RTM and the site selection effects (unless the reference group is characterized by the same effects as the treatment group, see Lord and Kuo, 2012). This method also requires more resources since data need to be collected at a large number of sites. Hence, it is not as popular due to the increase in data collection costs and database management.

2.4 BEFORE-AFTER STUDY WITH EMPIRICAL BAYES METHOD

The third method consists of incorporating the before-after study with the EB method in order to minimize the RTM described above (Hauer, 1997; Persaud et al., 2001). For this method, the data collection requirements may be larger than for the reference group since a very large amount of data need to be collected for developing reliable regression models (Lord, 2006). This method allows the estimation of the safety benefits at treated sites using information from reference sites. The expected crash frequency ($E[k|K]$) at a treated site is a result of the combination of the predicted crash count ($E[k]$) based on the reference sites with similar traits and the crash history (K) of that site. It should be noted that the terms κ and $E[\kappa]$ are technically the same, but the latter is usually used for statistical models. Hence, for the EB method, we will use $E[\kappa]$ rather than κ. The expected crash frequency and its variance are shown in Equations (9) and (10), respectively.

$$E[k|K] = w \cdot E[k] + (1-w) \cdot K \quad (9)$$
$$Var[k|K] = (1-w) \cdot E[k|K] \quad (10)$$

where w is a weight factor between 0 and 1

The parameter $E[k]$ is estimated from the safety performance functions (SPFs) developed using a negative binomial (NB) regression (also known as Poisson-gamma) model under the assumption that the covariates in the SPFs represent the main safety traits of the reference sites (Lord and Mannering, 2010). The procedure for using the before-after study with the EB method is described using the following steps.

Step 1. Develop Safety Performance Functions

Using crash, traffic, and geometric data from the reference sites, develop SPFs using NB regression models for all crashes, angle and turning crashes, and rear-end crashes. The NB regression model is the most common type of model used by transportation safety analysts for modeling traffic crashes (Lord and Mannering, 2010). This model is preferred over other mixed-Poisson models since the gamma distribution is the conjugate of the Poisson distribution. The NB regression model has the following modeling structure: the number of crashes 'Y_{it}' for a particular i^{th} site and time period t when conditional on its mean $E[k]_{it}$ is Poisson distributed and independent over all sites and time periods.

$$Y_{it}|E[k]_{it} \sim Poisson(E[k]_{it}) \quad i = 1, 2, ..., i \text{ and } t = 1, 2, ..., t \quad (11)$$

The mean of the Poisson is structured as:

$$E[k]_{it} = f(X;\beta)\exp(e_{it}) \quad (12)$$

where,

$f(.)$ is a function of the explanatory variables (X);

β is a vector of unknown coefficients; and,

e_{it} is the model error independent of all the covariates.

Although different functional forms were evaluated, the functional forms that provided the best statistical fit used for each crash type in this study are as follows:

$$E[k]_{all} = \mathrm{e}^{\beta_{all}} \times \mathrm{n} \times \left(\mathrm{F_{maj}} + \mathrm{F_{min}}\right)^{\beta_{tot\_all}} \times \left(\frac{\mathrm{F_{min}}}{\mathrm{F_{maj}} + \mathrm{F_{min}}}\right)^{\beta_{rat\_all}} \times \mathrm{e}^{\beta_{ror\_all}\mathrm{I_{ror\_proh}}} \quad (13)$$

$$E[k]_{AT} = \mathrm{e}^{\beta_{at}} \times \mathrm{n} \times \left(\mathrm{F_{maj}} + \mathrm{F_{min}}\right)^{\beta_{tot\_at}} \times \left(\frac{\mathrm{F_{min}}}{\mathrm{F_{maj}} + \mathrm{F_{min}}}\right)^{\beta_{rat\_at}} \times \mathrm{e}^{\beta_{ror\_at}\mathrm{I_{ror\_proh}}} \quad (14)$$

$$E[k]_{RE} = e^{\beta_{re}} \times \mathrm{n} \times \left(\mathrm{F_{maj}}\right)^{\beta_{maj}} \times (\mathrm{F_{min}})^{\beta_{min}} \times e^{\beta_{spd}\mathrm{S_{maj}} + \beta_{after}\mathrm{I_{after}}} \tag{15}$$

where,

$E[k]_{all}$ = expected crash frequency of all crash types;
$E[k]_{AT}$ = expected crash frequency of angle and turning crash types;
$E[k]_{RE}$ = expected crash frequency of rear-end crash types;
n= number of years of crash data;
$\mathrm{F_{maj}}$= annual average daily traffic of the major street (veh/day);
$\mathrm{F_{min}}$= annual average daily traffic of the minor street (veh/day);
$\mathrm{I_{ror\_proh}}$= indicator variable for right-turn-on-red prohibition (=1 if prohibited always, =0 otherwise);
$\mathrm{S_{maj}}$= posted speed limit on the major street (miles/hour);
$\mathrm{I_{after}}$= indicator variable for the after period (=1 if period in 2010-2012, =0 if period in 2005-2007); and,
β_i= vector of unknown coefficients (to be estimated).

Step 2. Estimate the expected number of crashes in the before period

Using the SPFs developed in Step 1, estimate the expected number of crashes ($E[k]_i$) for the before period at each treatment site. Obtain an EB estimate of the expected number of crashes ($E[\hat{k}_i|K_i]$) before implementation of the countermeasure at each treatment site and an estimate of variance of $E[\hat{k}_i|K_i]$. Recall that "^" refers to an estimate of a variable.

The estimate $E[\hat{k}_i|K_i]$ is given by combining the SPF predictions for the before period ($E[k]_i$) with the total count of crashes during the before period (K_i) as follows:

$$E[\hat{k}_i|K_i] = \hat{w}_i \cdot E[\hat{k}_i] + (1 - \hat{w}_i) \cdot K_i \tag{16}$$

The weight $\hat{w}_i$ is given by

$$\hat{w}_i = \frac{1}{1+\frac{E[\hat{k}_i]}{\phi}} \tag{17}$$

where ϕ is the inverse dispersion parameter of a NB regression model (i.e., $Var[Y_i] = E[k_i] + E[k_i]^2/\phi$).

The variance of the estimate is given as

$$Var[E[\hat{k}_i|K_i]] = (1 - \hat{w}_i) \cdot E[\hat{k}_i|K_i] \tag{18}$$

Step 3. Calculate the proportion of the after period crash estimate to the before period estimate

Using the SPFs developed in Step 1, estimate the expected number of crashes $(E[z]_i)$ in the after period at each treatment site. The ratio between the after period crash estimate and the before period estimate (P_i) is calculated as

$$P_i = \frac{E[\hat{z}]_i}{E[\hat{k}]_i} \tag{19}$$

Step 4. Obtain the predicted crashes ($\hat{\pi}_i$) and its estimated variance

Calculate the predicted crashes during the after period that would have occurred without implementing the countermeasure (i.e., red-light running cameras).

The predicted crashes ($\hat{\pi}_i$) are given by:

$$\hat{\pi}_i = P_i \times E[\hat{k}_i|K_i] \tag{20}$$

The estimated variance of $\hat{\pi}_i$ is given by:

$$Var[\hat{\pi}_i] = {P_i}^2 Var\left[E[\hat{k}_i|K_i]\right] = {P_i}^2(1-\hat{w}_i) \cdot E\left[\hat{k}_i\middle|K_i\right] \tag{21}$$

Step 5. Compute the sum of the predicted and observed crashes over all sites in the treatment group

The after-period crashes and their variances for a group of sites had the treatment not been implemented at the treated sites is given as:

$$\hat{\pi} = \sum_{i=1}^{j} \hat{\pi}_i \tag{22}$$

where j represents the total number of sites in the treatment group, and $\hat{\pi}$ is the expected after-period crashes at all treated sites had there been no treatment, as described above.

For a treated site, the crashes in the after-period are influenced by the implementation of the treatment. The safety effectiveness of a treatment is known by comparing the actual crashes with the treatment to the expected crashes without the treatment. The number of after-period crashes for a group of treated sites is given as:

$$\hat{\lambda} = \sum_{i=1}^{j} L_i \tag{23}$$

where L_i is the crash frequency during the after period at site *i*. The estimate of $\hat{\lambda}$ is equal to the sum of the observed number of crashes at all treated sites during the after study period.

Step 6. Estimate $Var[\hat{\lambda}]$ *and* $Var[\hat{\pi}]$

Based on the assumption of a Poisson distribution, the estimate of variance of $\hat{\lambda}$ is assumed to be equal to L. The estimate of variance of $\hat{\pi}$ can be calculated from the equation as follows:

$$Var[\hat{\lambda}_i] = L_i \tag{24}$$

$$Var[\hat{\lambda}] = \sum_{i=1}^{j} Var[\hat{\lambda}_i] \tag{25}$$

$$Var[\hat{\pi}_i] = (1 - \widehat{w}_i) \cdot E[\hat{k}_i | K_i] = (1 - \widehat{w}_i) \cdot \hat{\pi}_i \tag{26}$$

$$Var[\hat{\pi}] = \sum_{i=1}^{j} Var[\hat{\pi}_i] \tag{27}$$

Step 7. Estimate $\hat{\delta}$ *and* $\hat{\theta}$

The 'change in the safety' (δ) and 'index of safety effectiveness' (θ) are calculated as described above:

$$\hat{\delta} = \hat{\pi} - \hat{\lambda} \tag{28}$$

$$\hat{\theta} = \frac{\left(\frac{\hat{\lambda}}{\hat{\pi}}\right)}{\left(1 + \frac{Var(\hat{\pi})}{\hat{\pi}^2}\right)} \tag{29}$$

If $\hat{\delta}$ is greater than zero and $\hat{\theta}$ is less than one, then the treatment has a positive safety effect. In addition, the percent decrease in the number of target crashes due to the treatment is calculated as $100(1 - \hat{\theta})\%$.

Step 8. Estimate $Var[\hat{\delta}]$ *and* $Var[\hat{\theta}]$

The estimated variance and standard error of the estimated safety-effectiveness are given by:

$$Var[\hat{\delta}] = \hat{\pi} + \hat{\lambda} \tag{30}$$

$$Var[\hat{\theta}] = \frac{\hat{\theta}^2 \cdot \left[\frac{Var(\hat{\lambda})}{\hat{\lambda}^2} + \frac{Var(\hat{\pi})}{\hat{\pi}^2}\right]}{\left[1 + \frac{Var(\hat{\pi})}{\hat{\pi}^2}\right]^2} \tag{31}$$

$$s.e[\hat{\theta}] = \sqrt{Var[\hat{\theta}]} \tag{32}$$

The 95% confidence interval for $\hat{\theta}$ is calculated as $\hat{\theta} \pm 1.96 s.e[\hat{\theta}]$. If the confidence interval contains the value one, then no significant effect has been observed at the 5% level.

It should be pointed out that the EB method may not account for the site selection bias (Lord and Kuo, 2012). Examining the site selection effects on the EB estimate was beyond the scope of this study. Further discussion on this bias is presented in the last section.

3.0 DATA CHARACTERISTICS

The Chicago Tribune collected data at 116 signalized intersections for the treatment group and at 60 intersections for the reference group. Several variables were collected. They included entering traffic flow in vehicles per day (Annual Average Daily Traffic or AADT) by approach, number of lanes, presence of right-turn-on-red prohibition, number of lanes, median, left-turn lanes among others. As discussed above, the data collected by the Chicago Tribune was considered to be of good quality.

Figure 1 shows the location of the intersections where one or more RLCs were put in operation in 2008 or 2009, as well as whether or not the site was included in the initial data collection process. Figure 2 shows the location of the sites included in the reference group.

Following a cursory review of the data, only 4-legged signalized intersections were included in the analyses; Table 2 summarizes the number of intersections as a function of the number of legs at the intersection. 3-, 5- and 6-legged intersections were removed since the reference group only included, with the exception of one site, 4-legged signalized intersections. As discussed above, the reference group is needed for the before-after study with reference group and the EB method.

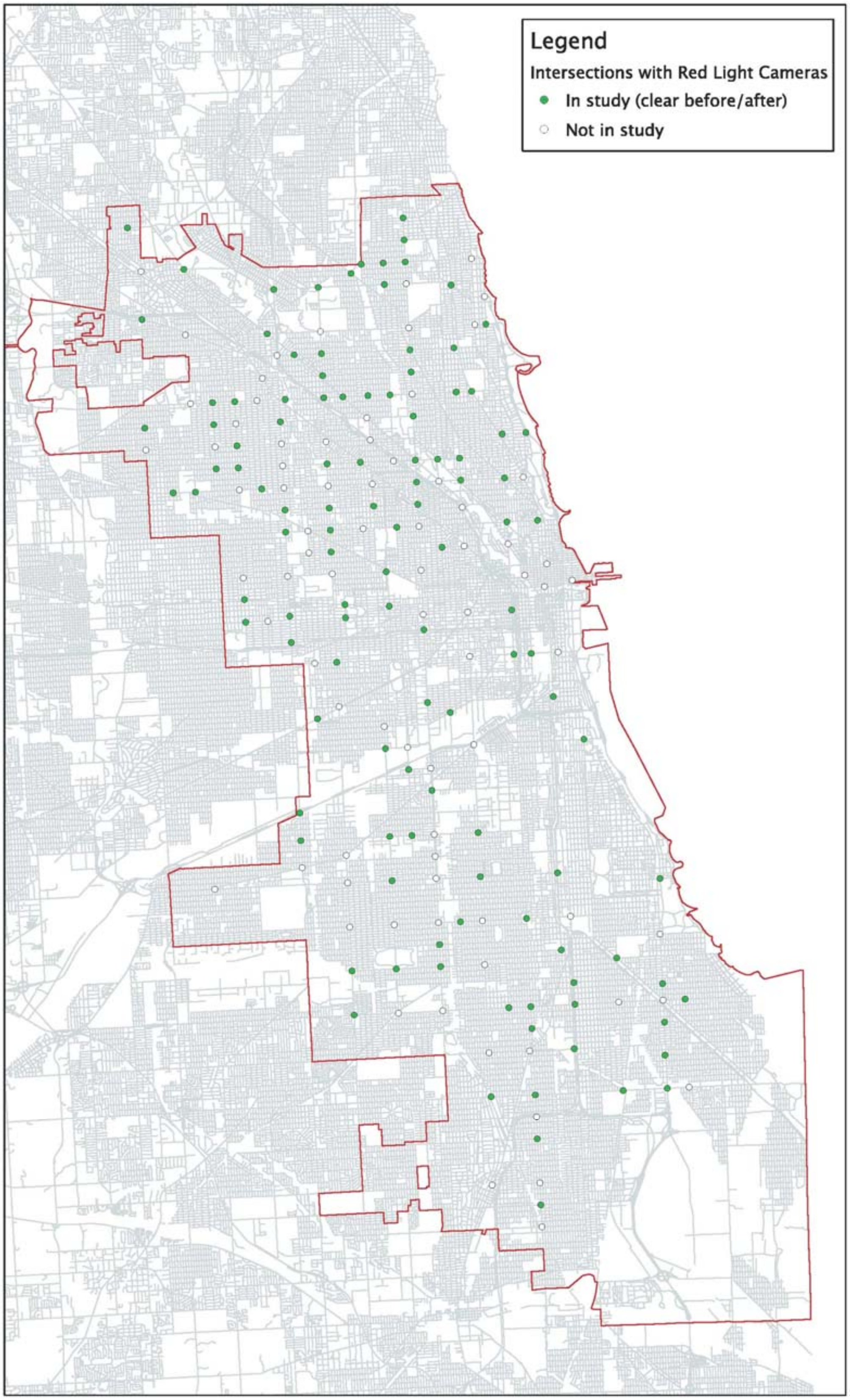

Figure 1. Location of Red-Light Cameras in Chicago

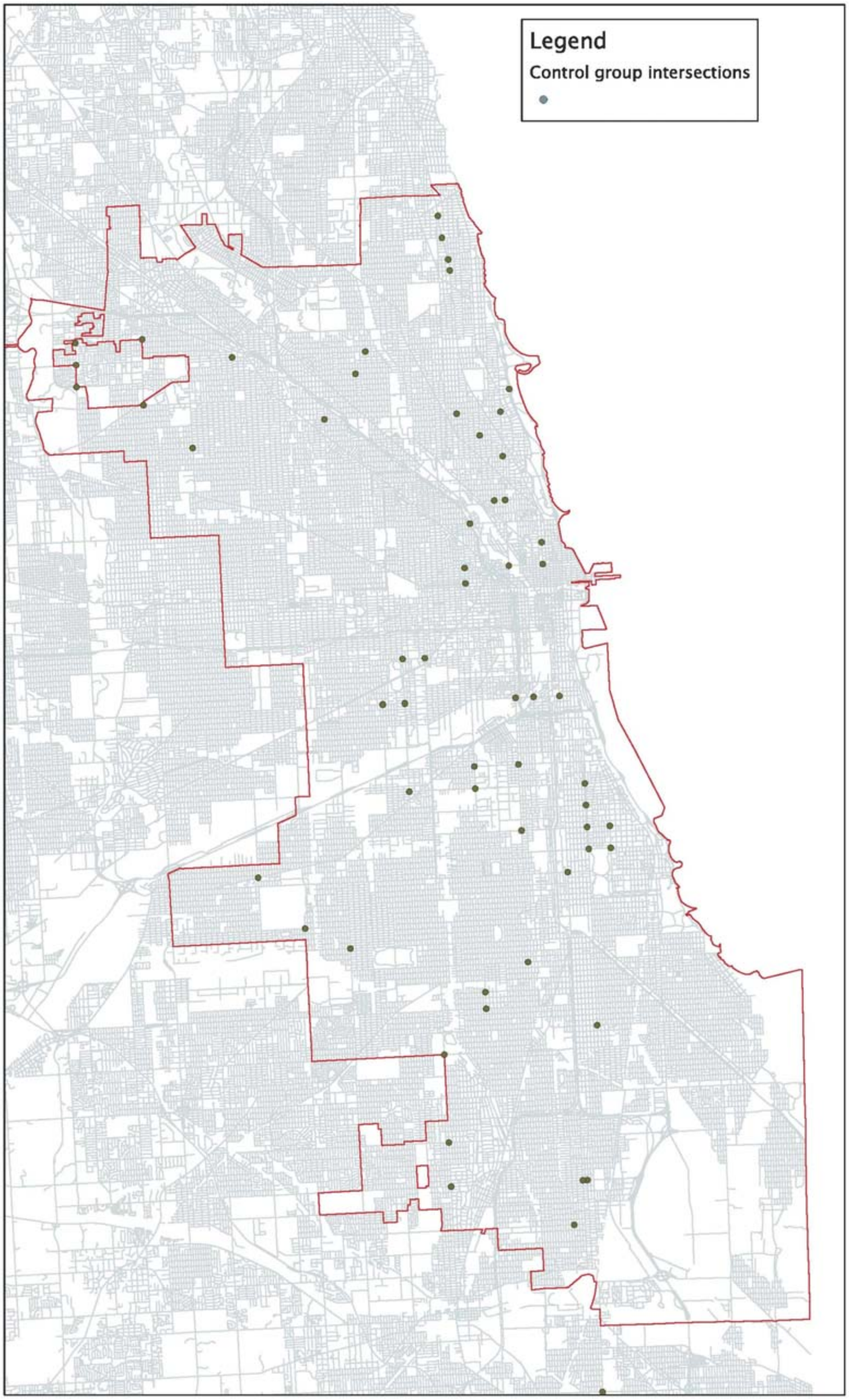

Figure 2. Location of Signalized intersections Included in the Reference Group

Table 2. Number of Intersections as a Function of the Number of Legs

Number of Legs	Number of Sites
3	4
4	103
5	2
6	7
Total	116

The next step consisted of filling out missing traffic flow volumes for the 4-legged signalized intersections. In both before and after evaluation periods, three years of data were considered (i.e., 2005 to 2007 for the before period and 2010 to 2012 for the after period). In most cases, all the independent variables (other than the RLCs), except traffic volumes, remained the same in the three-year period.

In this study, as in most traffic safety studies, traffic volume data were not available for all years of the evaluation period. The following rules were used to compute the average traffic volume values:

- If the volume is available for all three years or just the starting and ending years, then an average volume is used.
- If the volume is available for just the middle year or the middle year and one of starting or ending years, then the middle year is used.
- If the volume for the major street is available for multiple years but not for the minor street then the same change in the volumes is considered.
- If the volumes for the minor street are totally missing, then the volume of nearby similar intersection is considered.

From 103 treatment sites (4-legged signalized intersections), 13 sites were removed from the analyses because of missing data for some important variables. Thus, only 90 4-legged intersections could be used in the before-after studies.

The summary statistics of the variables collected by the Chicago Tribune are presented in Tables 3 and 4 for the explanatory and dependent variables, respectively. The explanatory variables include variables that describe the characteristics of the intersections, such as traffic flow and turning lanes. The dependent variables are the number of crashes by collision types: all crashes (defined as Total crashes below), read-end, angle, turning (left-through collisions), and others (e.g., side-swipe, fixed object, pedestrians, bicycles, etc.). The crash data collected only included injury-related collisions (KABC or killed, injury type A, injury type B, and injury type C). Property Damage Only (PDO) crashes were not included in this study because they are often significantly under-reported. It should be noted that this table shows that the average entering AADT decreased by about 4% to 8% between the 2006-2007 and 2010-2012 time periods, which coincides with the significant economic recession that started at the end of 2008.

Table 3. Summary Statistics of Explanatory Variables

Street	Variable	Statistic/ Condition	Treatment (90 sites)	Reference (59 sites)
MAJOR	Average AADT [2005-2007] (veh/day)	Minimum	7,000	10,100
		Maximum	55,500	61,000
		Mean	24,200	22,809
		Std. dev	9,243	9,526
	Average AADT [2010-2012] (veh/day)	Minimum	5,625	10,000
		Maximum	58,750	56,800
		Mean	23,154	21,587
		Std. dev	9,463	8,693
	Number of Lanes	Minimum	2	2
		Maximum	8	6
		Mean	3.6	3.2
		Std. dev	1.1	1.2
	Right-Turn-on-Red (proportion of intersections)	Prohibited	9%	8.5%
		Limited	18%	20.5%
		Allowed	73%	71.0%
	Left Turn Lane (proportion of intersections)	Not Present	8%	15%
		Present	92%	85%
	Right Turn Lane (proportion of intersections)	Not Present	94%	95%
		Present	6%	5%
	Median Presence (proportion of intersections)	None	60%	80%
		Painted	19%	5%
		Raised	21%	15%
	Posted Speed Limit (miles/hr)	Minimum	20	30
		Maximum	35	35
		Mean	29.9	30.5
		Std. dev	2.1	1.5
MINOR	Average AADT [2005-2007] (veh/day)	Minimum	375	4,800
		Maximum	40,150	27,500
		Mean	17,022	14,070
		Std. dev	5,989	4,872
	Average AADT [2010-2012] (veh/day)	Minimum	356	2,775
		Maximum	38,300	25,200
		Mean	16,136	13,333
		Std. dev	6,260	4,988
	Number of Lanes	Minimum	2	2
		Maximum	6	4
		Mean	2.6	2.7
		Std. dev	1.0	1.0
	Right-Turn-on-Red (proportion of intersections)	Prohibited	10%	12%
		Limited	19%	19%
		Allowed	71%	69%
	Left Turn Lane (proportion of intersections)	Not Present	13%	15%
		Present	87%	85%
	Right Turn Lane	Not Present	90%	97%

Street	Variable	Statistic / Condition	Treatment (90 sites)	Reference (59 sites)
	(proportion of intersections)	Present	10%	3%
	Median Presence (proportion of intersections)	None	95%	80%
		Painted	2%	7%
		Raised	3%	13%

Note: Only 4-legged intersections that had complete data were included.

Table 4. Summary Statistics of Dependent Variables

Period	Crash Type (KABC)	Statistic	Treatment (90 sites)	Reference (59 sites)
BEFORE	**Total**	Minimum	3	1
		Maximum	37	38
		Mean (Std. dev)	13.6 (6.9)	9.2 (6.1)
		Total	1228	540
	Rear-end	Minimum	0	0
		Maximum	14	9
		Mean (Std. dev)	2.1 (1.9)	1.5 (1.9)
		Total	190	90
	Angle and Turning	Minimum	0	0
		Maximum	25	22
		Mean (Std. dev)	7.2 (5.4)	4.4 (3.8)
		Total	646	262
	Other	Minimum	0	0
		Maximum	11	15
		Mean (Std. dev)	4.4 (2.7)	3.2 (2.3)
		Total	392	188
AFTER	**Total**	Minimum	2	2
		Maximum	34	22
		Mean (Std. dev)	11.8 (6.0)	8.5 (4.5)
		Total	1064	503
	Rear-End	Minimum	0	0
		Maximum	17	4
		Mean (Std. dev)	3.3 (2.9)	2.2 (2.1)
		Total	296	132
	Angle and Turning	Minimum	0	0
		Maximum	22	11
		Mean (Std. dev)	4.7 (3.6)	3.2 (2.5)
		Total	425	191
	Other	Minimum	0	0
		Maximum	12	11
		Mean (Std. dev)	3.8 (2.5)	3.1 (2.5)
		Total	343	180

Note: Only 4-legged intersections that had complete data were included.

4.0 ANALYSIS RESULTS

This section describes the results of the analyses. The first subsection presents relevant exploratory analyses, while the second subsection shows the results for the three types of before-after analyses.

4.1 EXPLORATORY ANALYSIS OF THE DATA

This subsection describes the results of the exploratory analysis conducted on the data and focuses on the crash rates calculated for the treatment and reference groups. The number of crashes at any given intersection are influenced by a number of factors, but entering traffic volumes (which is known as "exposure") usually have the greatest influence on the number of crashes (Hauer, 1997). The intersections in this database are of differing traffic volumes and change over time. Therefore, it is desirable to examine crash rates in order to better understand the differences between different time periods and between treatment and reference sites.

The crash rate at each intersection was calculated by dividing the number of crashes in any given crash category by the traffic volume, in this case, the annual entering traffic volume in vehicles per day. The number of crashes relative to the number of vehicle is very small, so the rates are typically expressed per 10 million vehicle miles, because the resulting values are more convenient to express and understand. The crash rate comparisons were done for all crashes, angle and turning collisions and rear-end collisions.

Crash rates may be interpreted as the probability (based on past events; in this case what occurred in a given period) of being involved in a crash per instance of the exposure measured. Observed crash rates are often used as a tool to identify and prioritize sites in need of modifications and for evaluation of the effectiveness of treatments.

Crash rates should be used with caution to assess risk. First, the crash rate method completely depends on the observed crash data, in this case from law enforcement reports submitted to the State. The issue of data quality and accuracy arises due to the limitations in recording, reporting, and measuring crash data with accuracy and consistency (for example, every crash may not result in a report). This issue is not specifically related to the data collected for this study, but applies to all crash databases used in highway safety research and analysis. As discussed above, this study only included injury crashes because the data are more reliable. It should be pointed out, however, that injury crashes can also be under-reported, although the magnitude is much smaller than for PDO crashes (Hauer and Heckert, 1987; Elvik and Myson, 1999).

Second, crash rates presume a linear relationship between crash frequency and the measure of exposure, which may not always be true. This basically means that there are proportionally less (or more) crashes per entering vehicles as the traffic flow increases and thus the crash risk per vehicle diminishes (or increases) when traffic flow increases; usually, the relationship is given by $\text{crashes} = \text{flow}^{\beta}$, where β is usually below 1.

Third, the method is affected by the limitations associated with natural variations in crash data, i.e. randomness in the data. The natural variations in the crash data results in the RTM bias described above when the data are analyzed sequentially (i.e., before-after).

Figure 3 shows the crash rates for the total number of crashes for the treatment and reference groups. The figure illustrates that the crash rates decreased by 11% between 2005-2007 and 2010-2012 for the treatment group.

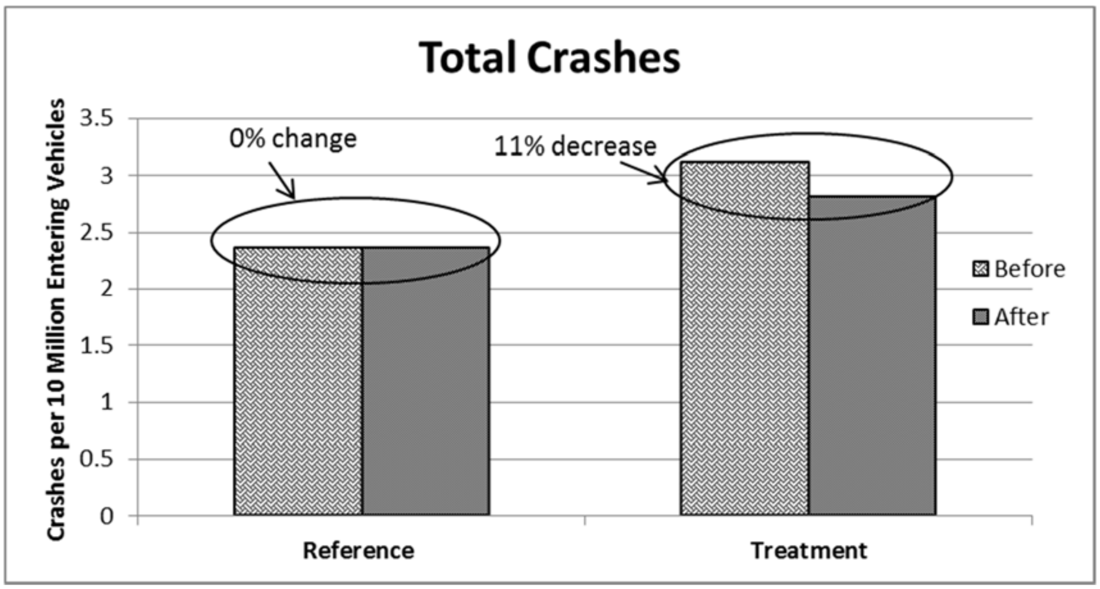

Figure 3. Crash Rates for Total Crashes (KABC)

Figure 4 shows the crash rates for the total number of rear-end injury crashes for the treatment and reference groups. The figure illustrates that the crash rates significantly increased for both groups. Potential factors explaining this characteristic for the reference group are discussed in the next section.

Figure 5 shows the crash rates for the total number of angle and turning injury crashes for the treatment and reference groups. The figure illustrates that the crash rates decreased for both groups, but was much more significant for the treatment group. A hypothesis explaining this characteristic for the reference group is discussed in the next section.

Figure 6 shows the crash rates for the total number of other injury crashes (i.e., pedestrian, side-swipe, etc.) for the treatment and reference groups. The figure illustrates that the crash rates decreased by 6% between 2005-2007 and 2010-2012 for the treatment group.

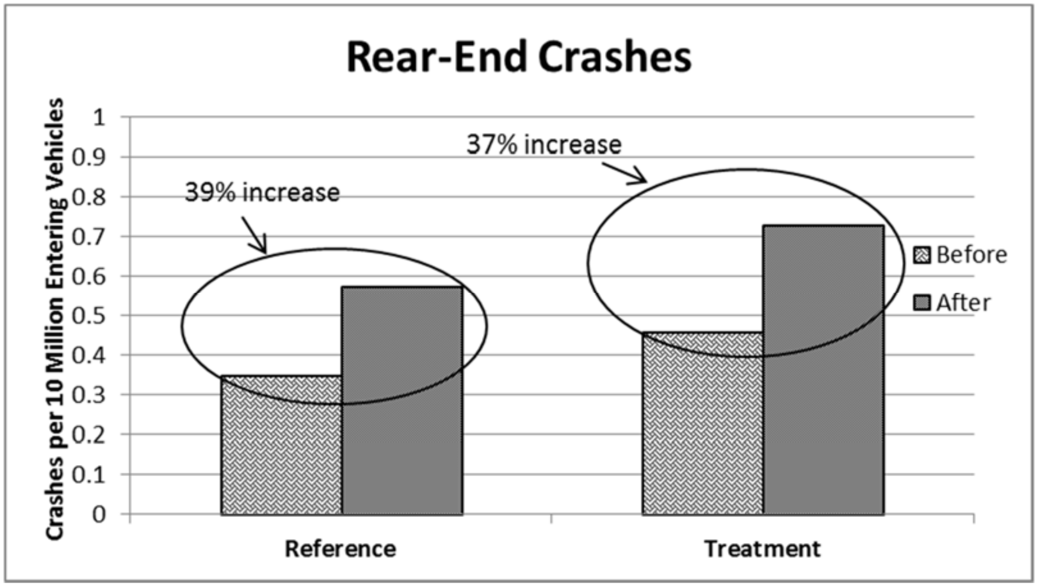

Figure 4. Crash Rates for Rear-End Crashes (KABC)

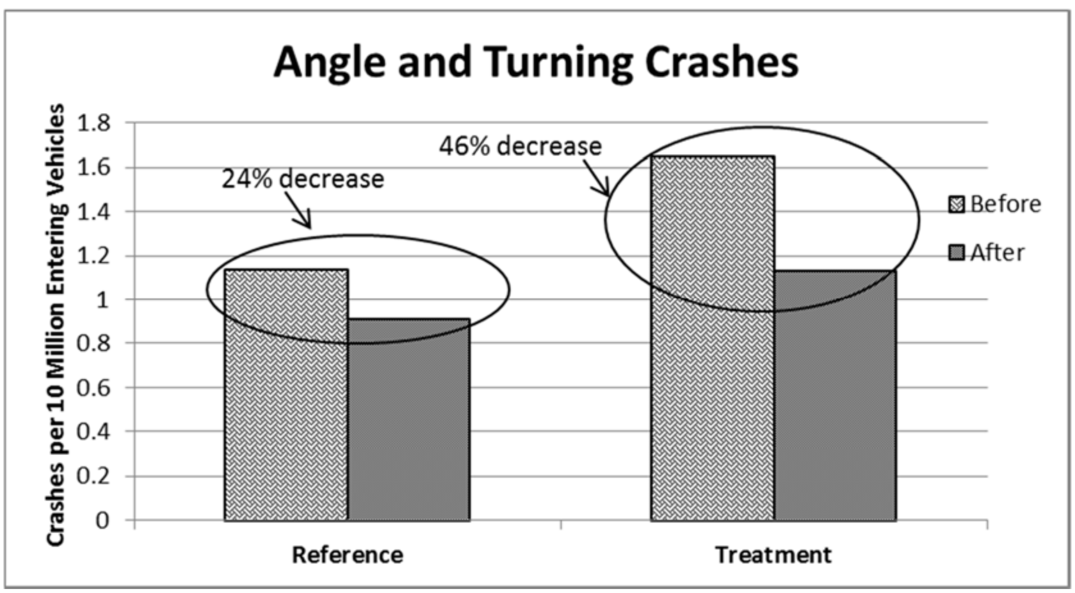

Figure 5. Crash Rates for Angle and Turning Crashes (KABC)

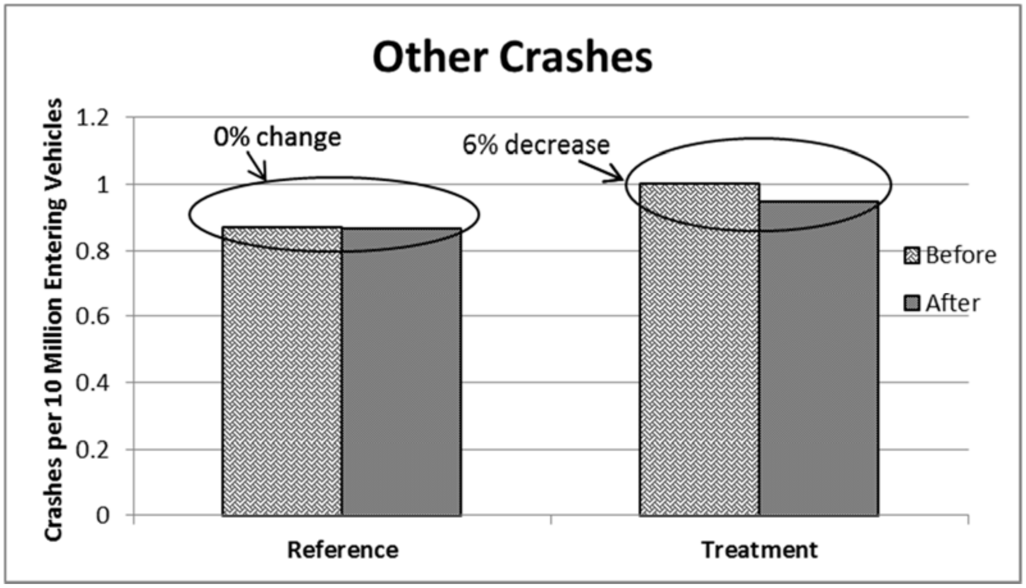

Figure 6. Crash Rates for Other Crashes (KABC)

4.2 BEFORE-AFTER STUDY: NAÏVE AND WITH REFERENCE GROUP

Using the methodology described in Sections 2.2 and 2.3, a naïve before-after study and one with the reference group were conducted based on the 90 sites where one or more RLCs were put in operation and the 59 sites that were part of the reference group. The analyses were performed for all injury (KABC) crashes (Total), rear-end, angle, turning and 'angle and turning'. The factor r_{tf} was calculated for each site and was adjusted to account for the potential non-linear relationship between exposure and safety, $r_{tf}^{0.8}$, described above. The factor r_d was equal to 1, since the time period was the same for both before and after the installation of the RLCs (3 years). The results are shown in Tables 5 to 9.

Table 5 shows the results for the total number of injury crashes. The naïve results indicate a reduction of 9% in total injury crashes that is statistically significant at the 5% level. When the reference group is included, a non-statistically significant reduction of 3% can be observed.

Table 6 shows the results for the number of angle injury crashes. The naïve results indicate a strong reduction of 41% in angle crashes that is statistically significant at the 5% level. However, when the reference group is included, a non-statistically significant reduction of 14% can be observed.

Table 5. Total Crashes (KABC) - Before-After Study (Naïve and Reference Group)

Variables	Treated Sites	Reference Group
Number of Crashes: Before	1,228	540
Number of Crashes: After	1,064	503
Ratio r_c		0.93
Predicted Crashes ($\hat{\pi}$)	1,171.4 (34.2)†	1091.2 (82.3)
Estimated Crashes ($\hat{\lambda}$)	1064 (32.6)	1064 (32.6)
Safety Index ($\hat{\theta}$)	<u>0.91</u>‡ (0.04)	0.97 (0.08)
Reduction in Crashes ($\hat{\delta}$)	<u>107.4</u> (47.3)	27.2 (88.6)

† Standard Deviation

‡ Underlined: statistically significant at the 5% level.

Table 6. Angle Crashes (KABC) - Before-After Study (Naïve and Reference Group)

Variables	Treated Sites	Reference Group
Number of Crashes: Before	261	124
Number of Crashes: After	146	83
Ratio r_c		0.67
Predicted Crashes ($\hat{\pi}$)	246.4 (15.7)	164.9 (26.2)
Estimated Crashes ($\hat{\lambda}$)	146 (12.1)	146 (12.1)
Safety Index ($\hat{\theta}$)	<u>0.59</u>† (0.04)	0.86 (0.15)
Reduction in Crashes ($\hat{\delta}$)	<u>100.4</u> (19.8)	18.9 (28.2)

† Underlined: statistically significant at the 5% level.

Table 7 shows the results for the number of turn injury crashes. The naïve results indicate a strong reduction of 24% in angle crashes that is statistically significant at the 5% level. However, when the reference group is included, a non-statistically significant reduction of 4% is noted.

Table 7. Turning Crashes (KABC) - Before-After Study (Naïve and Reference Group)

Variables	Treated Sites	Reference Group
Number of Crashes: Before	385	138
Number of Crashes: After	279	108
Ratio r_c		0.78
Predicted Crashes ($\hat{\pi}$)	365.4 (19.2)	286.0 (40.7)
Estimated Crashes ($\hat{\lambda}$)	279 (16.7)	279 (16.7)
Safety Index ($\hat{\theta}$)	<u>0.76</u>† (0.06)	0.96 (0.14)
Reduction in Crashes ($\hat{\delta}$)	<u>86.4</u> (25.4)	7.0 (44.0)

† Underlined: statistically significant at the 5% level.

Table 8 shows the results for the number of angle and turning injury crashes. The naïve results indicate a strong reduction of 41% in angle and turning crashes that is statistically significant at the 5% level. However, when the reference group is included, a non-statistically significant reduction of 6% can be observed.

Table 8. Angle and Turning Crashes (KABC) - Before-After Study (Naïve and Reference Group)

Variables	Treated Sites	Reference Group
Number of Crashes: Before	646	262
Number of Crashes: After	425	191
Ratio r_c		0.73
Predicted Crashes ($\hat{\pi}$)	611.8 (24.7)	446.0 (26.2)
Estimated Crashes ($\hat{\lambda}$)	425 (20.6)	425 (20.6)
Safety Index ($\hat{\theta}$)	<u>0.69</u>† (0.04)	0.94 (0.11)
Reduction in Crashes ($\hat{\delta}$)	<u>186.8</u> (32.2)	21.0 (52.4)

† Underlined: statistically significant at the 5% level.

Table 9 shows the results for the number of rear-end injury crashes. The naïve results indicate a strong increase of 61% in rear-end crashes that is statistically significant at the 5% level. However, when the reference group is included, a non-statistically significant increase of 8% is noted.

Table 9. Rear-End Crashes (KABC) - Before-After Study (Naïve and Reference Group)

Variables	Treated Sites	Reference Group
Number of Crashes: Before	190	83
Number of Crashes: After	296	124
Ratio r_c		1.47
Predicted Crashes ($\hat{\pi}$)	182.6 (13.5)	267.9 (26.2)
Estimated Crashes ($\hat{\lambda}$)	296 (17.2)	296 (17.2)
Safety Index ($\hat{\theta}$)	<u>1.61</u>[†‡] (0.15)	1.08[‡] (0.15)
Reduction in Crashes ($\hat{\delta}$)	<u>-113.4</u>[‡] (21.9)	-28.1[‡] (45.8)

[†] Underlined: statistically significant at the 5% level.
[‡] Shows an increase in the number of crashes.

The next subsection documents the application of the EB method for estimating the safety effects of the installation of RLCs. The EB method takes into consideration the RTM that cannot be handled with the two methods described above. It generally provides a more accurate estimate on the effects of these cameras on safety.

4.3 BEFORE-AFTER STUDY: EMPIRICAL BAYES METHOD

This subsection is divided into two parts. The first part covers the development of the regression or predictive models based on the data collected for the reference group. The second part covers the application of the EB method at the 90 signalized intersections where one or more cameras were utilized.

4.3.1 Crash Prediction Models

As described above, out of 60 reference sites, one site was excluded in the crash prediction model development because it was not a 4-legged signalized intersection. Due to the variability in traffic flows between the different time periods, the model development considered each period separately. Since each site is repeated twice, serial or temporal correlation may arise (Lord and Persaud, 2000). The researchers therefore developed Generalized Estimating Equation (GEE) models to account for the serial correlation, but the estimates were found to be not much different than the ones presented here. The total number of observations from which models are developed is 118. In total, three models were estimated: total or all injury crashes, angle and turning injury crashes together and rear-end injury crashes. The functional forms were presented in Equations (13) to (15) above.

Table 10 summarizes the results of the NB models. In all crash (Total) and angle and turning crash models, the total entering flow, the proportion of minor street flow at the intersection and the right-turn-on-red prohibition variables are significant. The indicator variable for representing the after study period is insignificant in these two models, which means there is no significant change in these crash types between the before and after time periods. The Pearson χ^2 statistic for the 'all crash' model is 117.98, and the degrees of freedom are 114 (= $n-p$ =118-4; here *n* and *p* are the number of observations and parameters respectively). As this statistic is less than $\chi^2_{0.05,114} = 139.92$, the hypothesis that the model fits the data cannot be rejected. One site was removed from the 'angle and turning crash' model as a result of an outlier analysis and thus the sample size used for the model was 116. Therefore, the degrees of freedom are 112 (= $n-p$ =116-4). The Pearson χ^2 statistic for the 'angle and turning' crash model is 125.96. As this statistic is less than $\chi^2_{0.05,112} = 137.70$, the hypothesis that the model fits the data cannot be rejected. The variables that are found to be significant to influence rear-end crashes are major street traffic flow, minor street flow, major street approach speed, and the indicator variable for the after period. The after period indicator variable suggests that the rear-end crashes increased in general at all similar intersections. The Pearson χ^2 statistic for the rear end crash model is 132.32, and the degrees of freedom are 113 (= $n-p$ =118-5). As this statistic is less than $\chi^2_{0.05,113} = 138.81$, the hypothesis that the model fits the data cannot be rejected.

Table 10. Estimates of the NB Model (Injury Crashes)

Crash Type	Parameter	Variable	Estimate	Std. Err†
ALL	β_0	Constant	-5.2134	1.4204
	β_{total}	Total entering volume	0.6516	0.1374
	β_{ratio}	Proportion of minor street volume	0.5209	0.1921
	β_{ror}	Right-turn-on-red prohibition	-0.2194	0.1493
	ϕ	Inverse dispersion parameter	7.2774	1.7235
		Pearson χ^2 =	117.98 ($\chi^2_{0.05,114} = 139.92$)	
ANGLE AND TURNING	β_0	Constant	-5.6259	2.1096
	β_{total}	Total entering volume	0.5951	0.2032
	β_{ratio}	Proportion of minor street volume	0.3400	0.2902
	β_{ror}	Right-turn-on-red prohibition	-0.3437	0.2325
	ϕ	Inverse dispersion parameter	3.2085	0.8130
		Pearson χ^2 =	125.96 ($\chi^2_{0.05,112} = 137.70$)	
REAR-END	β_0	Constant	-16.1810	2.6737
	β_{major}	Major street volume	0.7047	0.2586
	β_{minor}	Proportion of minor street volume	0.5824	0.2563
	β_{speed}	Major street approach speed	0.0922	0.0491
	β_{after}	After period effect	0.4965	0.1692
	ϕ	Inverse dispersion parameter	4.3007	2.0159
		Pearson χ^2 =	132.32 ($\chi^2_{0.05,113} = 138.81$)	

† Standard error of the parameter estimate

4.3.2 Before-After Analysis

Table 11 presents the average safety effect of the RLC enforcement systems at the 90 4-legged intersections in Chicago based on the EB method. This table shows that there are 1,064 crashes reported during the three year after study period at these 90 intersections (also discussed in the previous section). The analysis results show that if the treatment had not been used, the expected number of the crashes would have been 1,016 crashes during the three year after study period. In other words, it is estimated that RLCs increased the crashes by 5%. However, the standard deviation of this estimate is 4% which makes the estimate statistically insignificant at 5% level. This basically means the increase in crashes may not necessarily because of the treatment but may just have happened by chance.

Table 11. Results of the EB Analysis

Variables	All Crashes (KABC)	Angle and Turning Crashes (KABC)	Rear-End Crashes (KABC)
Number of Crashes: Before	1,228	646	190
Number of Crashes: After	1,064	425	296
Predicted Crashes ($\hat{\pi}$)	1016.4 (23.8)	500.6 (16.5)	241.7 (10.7)
Estimated Crashes ($\hat{\lambda}$)	1064 (32.6)	425 (20.6)	296 (17.2)
Safety Index ($\hat{\theta}$)	1.05[‡] (0.04)	0.85[†] (0.05)	1.22 (0.09)
Reduction in Crashes ($\hat{\delta}$)	-47.6[‡] (23.8)	75.6 (16.5)	-54.3 (10.7)

[†] Underlined: statistically significant at the 5% level.
[‡] Shows an increase in the number of crashes.

Table 11 also shows that, for angle and turning injury crashes, 425 crashes were reported in 2010 to 2012 at 90 treated intersections, and one would expect about 501 crashes had the treatment not been used. Thus, a reduction of about 76 crashes in three years is expected with the treatment. The average safety effects of the RLC enforcement show that, at the 5% level, there is a significant decrease in angle and turning injury crashes by 15%. On the other hand, an increase in rear-end injury crashes after the implementation of RLCs is observed. Overall, there were 296 rear-end crashes reported in the three year after study period, and one would expect about 242 crashes had there been no treatment. Thus, 54 more rear-end crashes occurred at the treatment intersections since the red light camera installation. The average safety effect of RLC systems on rear-end injury crashes is estimated to be an increase in crashes by 22%. This result is significant at 5% confidence level.

The researchers conducted additional analyses to see when the RLCs are more effective on safety. Ko et al. (2013) suggested that a significant safety benefit for RLCs is achieved if intersections have four or more red-light-related crashes per year (all crash severity levels). To evaluate this, intersections were separated based on the crash counts in the before period into two categories: one with intersections having greater than or equal to 4 injury crashes annually, and the other with intersections having fewer than 4 injury crashes annually. Although only injury crashes were used in this study, the same entry criterion proposed by Ko et al. (2013) can be used here. Table 12 presents the results of these analyses. When intersections with at least 4 injury crashes per year are considered, there is no significant change in all injury crashes, whereas angle and turning injury crashes decreased by 24%. This result is significant at the 5% level. Rear-end injury crashes increased by 20%; however, this result is marginally significant. Interestingly, these values are closer to the ones presented in the Highway Safety Manual (HSM) (AASHTO, 2010). The HSM suggests that RLCs would typically be expected to reduce right-angle collisions by 26% and increase rear-end collisions by

18%. It also suggests that there is no evidence that the red light camera installation affects other collision types.

When intersections experiencing fewer than 4 injury crashes per year are considered, there is a significant increase in all crashes by 19% after the installation of RLCs. Although the results show that both the angle and turning, and rear-end injury crashes increased after the installation of RLCs, the results are not significant at 5% level.

Table 12. Results of EB analysis for Different Entry Criteria

Intersections with Crashes $\geq$ 4 per year			
Variables	**All Crashes (KABC)**	**Angle and Turning Crashes (KABC)**	**Rear-End Crashes (KABC)**
Number of Crashes: Before	880	486	134
Number of Crashes: After	649	263	179
Predicted Crashes ($\hat{\pi}$)	668.1 (19.3)	345.4 (13.8)	148.2 (8.6)
Estimated Crashes ($\hat{\lambda}$)	649 (25.5)	263 (16.2)	179 (13.4)
Safety Index ($\hat{\theta}$)	0.97 (0.05)	<u>0.76</u> (0.06)	1.20 (0.11)
Reduction in Crashes ($\hat{\delta}$)	19.1 (19.3)	<u>82.4</u> (13.8)	<u>-30.8</u> (8.6)
Intersections with Crashes $<$ 4 per year			
Variables	**All Crashes (KABC)**	**Angle and Turning Crashes (KABC)**	**Rear-End Crashes (KABC)**
Number of Crashes: Before	359	160	60
Number of Crashes: After	427	166	120
Predicted Crashes ($\hat{\pi}$)	357.9 (14.0)	156.9 (9.2)	96.4 (6.5)
Estimated Crashes ($\hat{\lambda}$)	427 (20.7)	166 (12.9)	120 (11.0)
Safety Index ($\hat{\theta}$)	<u>1.19</u> (0.07)	1.05 (0.10)	1.24 (0.14)
Reduction in Crashes ($\hat{\delta}$)	<u>-69.1</u> (14.0)	-9.1 (9.2)	<u>-23.6</u> (6.5)

5.0 SUMMARY AND CONCLUSIONS

This report has documented a research study on the safety effects of the RLC program in Chicago, Illinois. The study was conducted on behalf of the Chicago Tribune, which collected data at 116 signalized intersections where one or more cameras were put in operation in 2008 or 2009, and at 60 sites that were used as reference group. The Chicago Tribune collected numerous variables before and after the installation of the cameras. Three years of data were collected for the before (2005-2007) and after (2010-2012) periods. After a cursory review of the data, 90 4-legged signalized intersections were used as the treatment group and 59 signalized 4-legged intersections for the reference group. Three types of before-after studies were conducted: 1) the naïve or simple before-after; 2) the before-after study with reference group; and, 3) the before-after study with the EB method.

The study results show that, based on the naïve estimate, a 9% reduction in the total number of injury crashes, a 41% percent reduction in angle and turning injury crashes, and a 61% increase in rear-end injury collisions were observed at the 90 signalized 4-legged intersections. However, when the reference group is included in the analysis and the EB method is used for estimating the effects of the enforcement program, a non-significant increase of 5% in the total number of injury crashes, a statistically significant reduction of 15% in angle and turning injury crashes, and a statistically significant increase of 22% in rear-end collisions were noted. The results shown based on the data collected by the Chicago Tribune are somewhat similar to some recent studies shown in the literature (e.g., Pulugurtha and Otturu, 2014; Høye, 2013; Erke, 2009; Council et al., 2005), but are also different than other studies that examined RLCs (e.g., Vanlaar et al., 2014; Shin and Washington, 2007; Retting and Kyrychenko, 2002). Table 13 summarizes the results of a few other studies that evaluated the influence of RLCs on crashes. All these studies indicate that RLCs have different safety effects based on where they are implemented (geographical, jurisdiction, etc.) and how they are implemented (criteria for selecting sites, such as those described in Pulugurtha and Otturu, 2014, and Ko et al., 2013).

TABLE 13. Summary of Research Studies on the Effects of RLCs on Safety (Ko et al., 2013)

Study	Number of sites	Method	Crash Reduction Percentage* (Crash Type)	Notes
Ng et al. (1997)	• 42 treated sites • 42 non-treated sites	CG Method	• 7% (all type) • 8% (RA)	No control for RTM and Spillover effect
Winn (1995)	• 6 treated sites • 6 non-treated sites	CG Method	• 63% (injury)	No control for RTM and Spillover effect
Walden (2012)	• 56 treated sites	Naïve comparison	• 30% (all type) • 43% (RA) • -5% (RE)	No control for RTM and Spillover effect
Retting and Kyrychenko (2002)	• 125 sites (11 treated sites)	Generalized linear regression model	• 7% (all type) • 32% (RA) • -3% (RE)	Control for RTM and Spillover effect, but the results are based on city-wide effects, not just at RLC sites
Hu et al. (2011)	• 14 cities with treatment • 48 cities without treatment	Poisson regression analysis	• 35% (fatality rate) for cities with treatment • 14% (fatality rate) for cities without treatment	Control for RTM and Spillover effect, but the results are based on city-wide effects, not just at RLC sites
Walden et al. (2012)	• 296 treated sites (39 communities)	CG method	• 26% (all type) • 19% (RA) • -44% (RE)	Partial control for RTM and Spillover effect
Washington and Shin (2005)	• 24 treated sites	CG method	• 42% (angle) • 10% (LT) • -51% (RE)	
		EB method	• 20%(angle) • 45%(LT) • -41% (RE)	Control for RTM and Spillover effect
Hallmark et al. (2010)	• 4 treated sites • 5 non-treated sites	Bayesian method	• 20% (all type) at treated sites • -7% (all type) at non-treated sites	Control for RTM
Persaud et al. (2005)	• 132 treated sites (7 jurisdictions)	EB method	• 25% (RA) • -15% (RE)	Control for RTM

NOTE: * negative values represent increase in crashes after the treatment.

The results of this study highlight further important discussion points. First, the economic downturn of 2008 seemed to have affected the exposure measured at signalized intersections. More specifically, the data collected showed a reduction in the traffic flow, in vehicles per day, in the order of 4% to 8% on average. This reduction influenced the before-after studies by increasing the index (θ) for total, angle, turning, rear-end injury crashes (r_{tf} is smaller than 1 on average). Second, the changes in angle, turning and rear-end injury collisions at the sites that were used for the reference group are very similar to the changes observed for the treatment group. It can be hypothesized that driver behavior may have also been affected at signalized intersections where no RLC was used. With so many cameras installed within a limited surface area (as seen in Figure 1), it may be possible that drivers changed the manner they approach and travel through all the signalized intersections located within the City of Chicago (227 square miles; Census 2014). It should be pointed out that research on spillover effects related to RLCs have so far provided mixed results. For example, Hoye (2013) found a weak relationship between intersections with and without RLCs, whereas Ko et al. (2013) found no effects. Therefore, further work should be done to explore this phenomenon in greater details, as it applies for this dataset.

In conclusion, similar to any research studies, the study is subjected to a few limitations. First, although the latest methodological tool was used for estimating the safety effects of RLCs, the EB estimate can still be biased, as documented in a recent research study (Lord and Kuo, 2012). The magnitude of the bias is very difficult to measure and further work is currently being conducted on this topic. Second, the regression models were estimated from observations that may have been influenced by the spillover effects. This means that the estimates calculated by the before-after study with reference group and the EB methods documented above may be underestimated. It is possible that using a different sample of signalized 4-legged intersections that is not influenced by the potential spillover effects could lead to different estimates. Despite these two limitations, the results nonetheless show that RLCs significantly reduce angle and turning injury collisions, but increase rear-end injury collisions as documented in the majority of the studies that examined the effects of RLCs on safety. Finally, the work done in this study only applies to signalized 4-legged intersections located within the City of Chicago. The results should not be generalized to other intersection types and outside the study area.

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REFERENCES

AASHTO (2010) Highway Safety Manual, 1st Ed. American Association of State Highway and Transportation Officials, Washington, D.C.

Cook, R., W. Wei (2002) Selection effects in randomized trials with count data. Statistics in Medicine, Vol. 21, pp. 515-531.

Council, F.M., B. Persaud, C. Lyon, K. Eccles, M. Griffith, E. Zaloshnja, T. Miller (2005) Implementing Red Light Camera Programs Guidance from Economic Analysis of Safety Benefits. Transportation Research Record 1922, pp. 38–43.

Davis, G. (2000) Accident reduction factors and causal inference in traffic safety studies: a review. Accident Analysis and Prevention, Vol.32, pp. 95–109.

Elvik, R., A.B. Myson (1999) Incomplete Accident Reporting: a Meta-Analysis of Made in Thirteen Countries. Transportation Research Record 1665, pp. 133-140.

Erke, A. (2009) Red light for red-light cameras? A meta-analysis of the effects of red-light cameras on crashes. Accident Analysis and Prevention, Vol. 41, pp. 897–905.

Hallmark, S., M. Orellana, E. Fitzsimmons, T. McDonald, D. Matulac (2010) Evaluating the Effectiveness of an Automated Red Light Running Enforcement Program in Iowa Using a Bayesian Analysis. Paper No.10-0489, TRB 2010 Annual Meeting CD-ROM, Washington, D.C.

Hauer, E. (1997) Observational Before-After Studies in Road Safety. Pergamon Publications, London.

Hauer, E., A.S. Heckert (1987) Extent and Some Implications of Incomplete Accident Reporting. Transportation Research Record 1185, pp. 1-8.

Høye, A. (2013) Still red light for red light cameras? An update. Accident Analysis and Prevention, Vol. 55, pp. 77– 89.

Hu, W., A.T. McCartt, E.R. Teoh (2011) Effects of Red Light Camera Enforcement on Fatal Crashes in Large US Cities. Journal of Safety Research, Vol. 42, pp. 277–282.

Ko, M., S.R. Geedipally, T.D. Walden (2013) Effectiveness and Site Selection Criteria of red Light Running Camera Systems. Transportation Research Record: 2327, pp. 53-60.

Lord, D. (2006) Modeling Motor Vehicle Crashes using Poisson-gamma Models: Examining the Effects of Low Sample Mean Values and Small Sample Size on the Estimation of the Fixed Dispersion Parameter. Accident Analysis and Prevention, Vol. 38, No. 4, pp. 751-766.

Lord, D., P-F. Kuo (2012) Examining the Effects of Site Selection Criteria for Evaluating the Effectiveness of Traffic Safety Improvement Countermeasures. Accident Analysis & Prevention, Vol. 47, pp. 52-63.

Lord, D., F. Mannering (2010) The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. Transportation Research - Part A, Vol. 44, No. 5, pp. 291-305.

Lord, D., B.N. Persaud (2000) Accident Prediction Models With and Without Trend: Application of the Generalized Estimating Equations (GEE) Procedure. Transportation Research Record 1717, pp. 102-108.

Ng, C.H., Y.D. Wong, K.M. Lum (1997) The Impact of Red Light Surveillance Cameras on Road Safety in Singapore. Journal Road Transport Research, Vol. 2, pp. 72–80.

Persaud B.N., R. Retting, P. Garder, D. Lord (2001) Observational before-after study of U.S. roundabout conversions using the empirical Bayes method. Transportation Research Record 1751, pp. 1-8.

Persaud, B., F.M. Council, C. Lyon, K. Eccles, M. Griffith (2005) Multijurisdictional Safety Evaluation of Red Light Cameras. Transportation Research Record 1922, pp. 29-37.

Pulugurtha, S.S., R. Otturu (2014) Effectiveness of red light running camera enforcement program in reducing crashes: Evaluation using “before the installation”, “after the installation”, and “after the termination” data. Accident Analysis and Prevention, Vol. 64, pp. 9– 17.

Retting, R.A., S.Y. Kyrychenko (2002) Reductions in Injury Crashes Associated with Red Light Camera Enforcement in Oxnard, California. American Journal of Public Health, Vol. 92, No. 11, pp. 1822-1825.

Shin, K, S. Washington (2007) The impact of red light cameras on safety in Arizona. Accident Analysis and Prevention, Vol. 39, pp. 1212–1221.

US Census (2014) http://quickfacts.census.gov/qfd/states/17/1714000.html (Accessed on Nov 2, 2014)

Vanlaar, V., R. Robertson, K. Marcoux (2014) An evaluation of Winnipeg’s photo enforcement safety program: Results of time series analyses and an intersection camera experiment. Accident Analysis and Prevention, Vol. 62, pp. 238– 247.

Walden, T.D. (2012) Analysis on the Effectiveness of Photographic Traffic Signal Enforcement Systems in Texas. Texas Transportation Institute, College Station, TX. (http://ftp.dot.state.tx.us/pub/txdot-info/trf/red_light/tti_evaluation.pdf)

Walden, T.D., S.G. Geedipally, M. Ko, R. Gilbert, M. Perez (2011) Evaluation of Automated Traffic Enforcement Systems in Texas. Texas Transportation Institute, College Station, TX. (http://ftp.dot.state.tx.us/pub/txdot-info/trf/red_light/auto_traffic.pdf)

Washington, S., K. Shin. (2005) The impact of Red Light Cameras (Automated Enforcement) on Safety in Arizona. Report No. 550, University of Arizona, Tucson, 2005.

Winn, R. (2011) Running the Red and Evaluations of Strathclyde Police's Red Light Camera Initiative. The Scottish Central Research Unit: Glasgow, Scotland, 1995. (http://www.scotland.gov.uk/cru/resfind/drf7-00.htm)