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Impact of Red-Light Cameras on Traffic Collisions in the City of Ottawa

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Abstract - The impacts of red-light cameras (RLCs) on overall signalized intersection safety are still debatable. This paper examines the safety impacts of RLCs using actual collision records for treated and untreated signalized intersections in Ottawa, Ontario, Canada. Direct regression analysis of collision data on treated intersections showed a significant impact for RLCs on angle, injury, and fatal collisions but no significant impact on other impact types and severity levels, a finding that was likely affected by the relatively small number of treated sites. On the other hand, an Empirical Bayes before-and-after study showed a significant impact for RLCs, where total and property damage only (PDO) collisions increased while injury and fatal collisions decreased. The impact of RLCs also depended on the collision type, where sideswipe, rear-end, and single motor vehicle collisions increased, but angle collisions decreased at RLC treated sites. It is therefore concluded that RLCs at signalized intersections in the study area reduced severe collisions involving injury or fatality while increasing PDO collisions.

***Keywords*:** Traffic safety, Red light cameras, Empirical Bayes, Before-and-after study

1 Introduction

Road crashes tend to cluster around intersections due to continuous stop-and-go traffic, unsafe road user behaviours, and some complicated conflicting movements. In Canada, intersections accounted for more than 30% of traffic fatalities and40% of severe injuries in 2009 [1]. Generally, one of the main factors contributing to intersection-related crashes is drivers'traffic violations. Specifically, red light running (RLR), when a driver does not stop and runs the red light at a signalized intersection, is one of the primary causes of such crashes [2]. The problem of RLR is a worldwide concern. In the USA, RLRcaused approximately 115,741 injuries and 928 deaths in 2020 [3]. Red-light cameras (RLCs) represent a countermeasure against RLR, which is being employed at a consistently increasing rate. A RLC is a traffic enforcement camera that takes photos of vehicles that enter an intersection in the red interval of the traffic signal, thus serving as a deterrent to drivers whopurposely run red lights [4]. Although RLCs are used for the main objective of reducing the number of RLR violations and associated crashes, their safety impacts remain debatable [5]. While many studies concluded that RLCs reduce crashes [6], other studies indicated that RLCs increase crashes or have negligible safety impacts [7],[8]. Several studies in the literature have assessed the safety impacts of RLCs with conflicting results including reduction of certain types of crashes coupled with increase of other types [5],[9]-[14]. Notably, RLCs often increase rear-end crashes because of sudden breaking [15]. Inaddition, while most studies reported a reduction in the more severe crashes involving injuries or fatalities [5],[9], others concluded an insignificant effect [15] or increase in these severe crashes [16].

In the review of previous work, it is noted that the impact of RLCs on the collision severities and impact types varied based on the methodologies and study areas. Therefore, the principal objective of this paper is to examine the expected benefits of RLCs as a safety improvement tool based on historical collision data in the City of Ottawa as a typical mid-size Canadian city. The paper evaluates the safety performance of RLCs in Ottawa by developing safety performance functions (SPFs) and performing a before-and-after study considering the potential contributing factors, such as geometric characteristics of the intersections and speed limits on the intersecting roads.

2 Study Methodology and Data Collection

2.1 Site Selection

This study is based in the City of Ottawa, Canada, where 70 RLCs are currently installed at signalized intersections. For the safety analysis, RLC intersections were selected based on the availability of traffic volume and collision data.Intersections with a maximum RLC installation year of 2017 were considered to ensure at least two full years of collision records prior to COVID-19 public health restrictions in 2020. Subsequently, 19 RLC intersections with installation years between 2011 and 2017 were selected and are referred to as the treated sites. Moreover, 40 signalized intersections without RLC were selected as a reference or comparison group. These intersections have similar characteristics to the treated sites interms of traffic volume, geometric design, and speed limit. Every intersection in this reference group is at least 800 m awayfrom the nearest treated intersection. All treated and reference intersections had a constant geometric design during the studyperiod. Figure 1 shows a map of the City of Ottawa with all RLC sites and the selected treated sites in this study.

2.2 Data Collection

Collision data from 2013 to 2019 were obtained from the Open Ottawa dataset [17]. An additional collision dataset and traffic volume data were provided by the Traffic Department of the City of Ottawa for the period of 2009 to 2012. Collision data shapefiles were imported into ArcGIS software to identify the intersection-related collisions, which were defined as those collisions within a specific distance from the intersection. Most studies have employed a buffer zone of 46 or 76 m around intersections. For example, a 76-m buffer zone is used in the Highway Safety Manual (HSM) [18]. However, such a buffer zone has the potential to create areas of overlap with adjacent intersections [19]. On the other hand, a 46-m buffer zone offers the advantages of reducing the likelihood of overlapping with adjacent intersections and reducing the probability of several collisions being classified incorrectly as intersection collisions in urban areas with a higher density street network. Therefore, a 46-m buffer zone was used to identify intersection crashes in this study. Collisions at each intersection were

Figure 1: RLCs within Ottawa, Canada, and Selected Sites.

classified based on impact type into four groups; namely, single motor vehicle, rear-end, angle, and sideswipe; and were classified based on severity to three levels; namely non-fatal injury, fatal+injury, and property damage only (PDO). Average annual daily traffic (AADT) and collision data included three years before and two or three years after RLC installation at treated sites and three continuous years for the reference group. Geometric characteristics of the intersections; namely the number of through, left turn, and right turn lanes; were collected manually from Google Earth Pro. Finally, the speed limits on the major and minor roads of each intersection were also collected from Google Maps.

2.3 Safety Performance Function (SPF)

The first approach used to examine the impacts of RLCs on traffic safety is regression analysis to develop safety performance functions (SPFs) including a parameter for the presence of RLC. Furthermore, SPF development using data from the reference (untreated) group is also a required step in the second approach which uses Empirical Bayes (EB) before-and-after study. In general, a SPF is a statistical model for predicting the frequency of collisions based on site-specific characteristics.

According to Lee et al. [12], it is important to make an acceptable selection of the dependent variable, independent variables, and the statistical model that effectively identifies the relationship between the dependent and independent variables to develop SPF accurately. AADT, geometric characteristics, and speed limit information all serve as independent variables, while annual collision frequency serves as the dependent variable. Modelling attempts in this paper accounted for the impact type and severity level by setting different dependent variables to correspond to each impact type and severity level in addition to all impact types and all severity levels combined. In selecting the statistical model, several issues with linear regression models have been widely documented in the literature, with Poisson or Negative Binomial (NB) regression widely accepted as the best approach for fitting collision data and developing SPFs [12].

Modelling collision frequency can be performed using either a Poisson or NB regression model, based on the over-dispersion parameter. If the value for over-dispersion does not change considerably from zero, the Poisson model can be an appropriate option. When the over-dispersion parameter exceeds zero, it would be reasonable to use a NB model [12]. The other phenomenon that might happen is the finding of no crashes in the collision data for a considerable portion of the sample. To address this issue, zero-inflated models may be used when developing SPF models using Poisson or NB distributions, but this was not applicable in this study because there were no sites with zero collisions. In all modelling attempts in this study, NB regression provided a better fit than Poisson regression, and all results presented in this paper correspond to NB regression.

2.4 Before-and-After Study

Three types of before-and-after studies exist in the literature. First, the naïve before-and-after study is the easiest method available for assessing the safety consequences of treatments [20]. This approach does not take into consideration changes in many factors from the "before" to the "after" periods [10]. Furthermore, the regression-to-mean (RTM) and site selection impacts are not taken into consideration. RTM is a common concern in before-and-after analyses evaluating the safety effects at treated locations, which likely already have higher crash frequencies and severities than other locations [12]. The second method is a before-and-after study with a reference group, which is partially similar to the naïve method but takes local and regional variations into account [16]. The third method is the EB before-and-after method (referred to in this paper simply as the EB method), which is a more credible method, and was selected for this study. The EB method is a meticulous technique for assessing the safety effects of a given treatment that has been extensively employed in contemporary traffic safety research, as shown in the review of RLC studies. The EB method is a statistical technique that considers RTM bias associated with safety impact assessment. In the EB method, variations in collision frequencies at treatment sites during the "before" and "after" periods are properly accounted for, which is one of this method's major advantages [5].

The EB method amalgamates the observed and predicted collision frequencies to estimate an unbiased expected crash frequency at each treated site in the "after" period if treatment had not been implemented. The predicted collision frequency is determined using a SPF normally developed using the reference group data. The expected collision frequency at a given location is then estimated as follows [18]:

$$N_{expected} = w.N_{predicted} + (1 - w)N_{observed} \quad (1)$$

Where $N_{expected}$ = estimate of expected average collision frequency for the "before" period; $N_{predicted}$ = predicted collisionfrequency for the "before" period; $N_{observed}$ = observed collision frequency over the "before" period; and w = computed weight factor, which is calculated using the following equation.

$$w = \frac{1}{1 + k \,.\, \sum_{all\ study\ years} N_{predicted}} \tag{2}$$

Where k = over-dispersion parameter of the associated SPF used to predict collision frequency.

The expected collision frequency ($N_{expected}$) should be normalized for the "after" period because it is an approximation regarding the duration of the "before" period. Therefore, the following equation is applied to estimate the "after" period crashes [21]:

$$\pi_i = N_{expected} \times \frac{AADT^{\alpha}_{after}}{AADT^{\alpha}_{before}} \tag{3}$$

Where π_i = expected number of collisions at treatment site i in the "after" period had a treatment not been implemented; α = regression coefficient of AADT from the SPF; and $AADT_{after}$ and $AADT_{before}$= AADT at the treatment site in the "after" and "before" periods, respectively.

The total expected number of collisions at all treatment sites in the "after" period (Π) is then calculated as follows:

$$\Pi = \sum_i \pi_i \tag{4}$$

3 Results and Discussion

As mentioned earlier, the safety analysis of the impacts of RLCs was performed using the actual collision records. Having collected the data of collisions, AADT, and geometric characteristics of the treated and reference sites, the two analysis approaches mentioned in the previous section were applied. This section first presents the NB regression results and the developed SPF for Ottawa's local conditions. Then, the results of the EB method are presented.

3.1 Regression Analysis and SPF

In this approach, the NB regression was used to develop SPFs that relate the annual collision frequency at a signalized intersection of the different impact types and severity levels to site characteristics. For general SPFs, the NB regression was performed using the data of the "before" and "after" periods of the 19 RLC (treated) intersections using STATA software. The safety treatment RLC was considered using a dummy independent variable (equal to 1 if RLC exists or 0 otherwise). Variables such as AADT, speed limit on the major and minor roads, and the number of through and protected left turn lanes were considered. Independent variables with a *p*-value greater than 0.10 were removed from the model. The Akaike Information Criterion (AIC) was used to compare the models' goodness-of-fit, where smaller AIC values suggest a better fit. Table 1 presents the independent variables included in the best fit models for collision frequencies classified based on collision impact type and severity level.

As shown in the table, each model has a number of significant independent variables. However, the RLC dummy variable was statistically significant only in angle, injury, and injury+fatal collisions. In all these three collision categories, the RLC variable has negative collisions indicating a reduction in expected collision frequency at intersections with RLC. Specifically, the coefficients indicate a reduction in collision frequency of 26% to 30% of these collision categories. Therefore, RLCs were associated with a decrease in the angle, injury, and fatal collisions.

Table 1: Final SPFs for the Different Collision Categories (Treated Sites in the Before and After Periods).

Final Model	Variable	Coefficient	p-value	Dispersion factor
Total Collisions[a]	$ln(AADT_{major})$	0.604	<0.001	0.055
	$ln(AADT_{minor})$	0.347	<0.001	
	$Speed_{minor}$	0.015	0.002	
	$Through\ lanes_{minor}$	0.236	0.001	
	$Left\ turn\ lanes_{minor}$	0.198	0.024	
	$Left\ turn\ lanes_{major}$	-0.242	0.001	
	Constant	-7.698	<0.001	
Rear-end Collisions[b]	$ln(AADT_{major})$	1.118	<0.001	0.283
	$ln(AADT_{minor})$	0.281	0.001	
	$Left\ turn\ lanes_{minor}$	0.272	0.064	
	$Speed_{minor}$	0.030	0.001	
	Constant	-13.841	<0.001	
Angle Collisions[b]	$ln(AADT_{minor})$	0.480	<0.001	0.067
	$Through\ lanes_{major}$	0.141	0.057	
	$Left\ turn\ lanes_{major}$	-0.223	0.037	
	RLC	-0.303	0.009	
	Constant	-2.692	<0.001	
Sideswipe Collisions[b]	$ln(AADT_{major})$	0.716	0.011	0.168
	$ln(AADT_{minor})$	0.815	<0.001	
	$Through\ lanes_{minor}$	0.337	0.045	
	$Left\ turn\ lanes_{major}$	-0.728	<0.001	
	Constant	-13.955	<0.001	
SMV Collisions[b]	$Speed_{minor}$	0.034	0.01	≈0
	$Through\ lanes_{minor}$	0.517	0.005	
	Constant	-3.054	<0.001	
PDO Collisions[c]	$ln(AADT_{major})$	0.702	<0.001	0.069
	$ln(AADT_{minor})$	0.355	<0.001	
	$Left\ turn\ lanes_{major}$	-0.269	0.001	
	$Speed_{minor}$	0.015	0.006	
	$Left\ turn\ lanes_{minor}$	0.206	0.035	
	$Through\ lanes_{minor}$	0.225	0.008	
	Constant	-8.958	<0.001	
Non-Fatal Injury Collisions[c]	$ln(AADT_{minor})$	0.343	<0.001	≈0
	$Through\ lanes_{major}$	0.230	0.003	
	$Speed_{minor}$	0.017	0.043	
	RLC	-0.256	0.07	
	Constant	-3.442	<0.001	
Injury+Fatal Collisions[c]	$ln(AADT_{minor})$	0.347	<0.001	≈0
	$Through\ lanes_{major}$	0.241	0.002	
	$Speed_{minor}$	0.017	0.042	
	RLC	-0.265	0.06	
	Constant	-3.498	<0.001	

[a] All collision severities and all impact types.
[b] All collision severities corresponding to a specific impact type.
[c] All collision impact type corresponding to a specific severity level.

3.2 EB Before-and-After Approach

As explained earlier, for the EB study, NB regression was first performed using the data of the 40 intersections in the reference (untreated) group only using STATA software. Independent variables with a p-value greater than 0.10 were removed from the model one at a time. AIC was used to compare the models' goodness-of-fit, where smaller AIC values suggest a better fit. Table 2 presents the final models for annual collision frequencies classified based on impact type and severity level.

Having established the SPFs based on the reference group data, the number of expected collisions if the treatment was not implemented and the percentage of change of collision frequency was estimated for the treated sites as shown in Table 3. Based on these results, RLCs on average increased total collisions by about 9%. However, considering collision severity,a reduction of 10% was observed in injury and injury+fatal collisions, while PDO collisions increased by 16%. The results also indicate that RLC significantly increased sideswipe and rear-end collisions by about 39% and 7%, while significantly reducing angle collisions by about 15%. The results also indicate that RLC increased single motor vehicle collisions by 12%,the 95% confidence interval for the treatment effectiveness (θ) is 0.87-1.37, suggesting that this effect is not statistically significant at a 5% level of significance.

Table 2: Final SPF Models for Annual Collision Frequency for EB Before-and-After Study

Final Model	Variable	Coefficient	p-value	Dispersion factor
Total Collisions[a]	$ln(AADT_{major})$	0.906	<0.001	0.045
	$ln(AADT_{minor})$	0.747	<0.001	
	$Left\ turn\ lanes_{major}$	-0.187	0.009	
	Constant	-13.388	<0.001	
Rear-end Collisions[b]	$ln(AADT_{major})$	1.211	<0.001	0.108
	$ln(AADT_{minor})$	0.838	<0.001	
	Constant	-18.192	<0.001	
Angle Collisions[b]	$ln(AADT_{total})$	0.840	<0.001	0.237
	$Speed_{minor}$	0.014	0.008	
	$Left\ turn\ lanes_{major}$	-0.558	<0.001	
	Constant	-7.836	<0.001	
Sideswipe Collisions[b]	$ln(AADT_{major})$	1.593	<0.001	0.064
	$ln(AADT_{minor})$	0.847	<0.001	
	$Speed_{major}$	-0.019	0.011	
	$Left\ turn\ lanes_{minor}$	-0.461	0.019	
	$Through\ lanes_{minor}$	0.317	0.077	
	Constant	-22.359	<0.001	
Single Motor Vehicle Collisions[b]	$ln(AADT_{minor})$	0.523	0.009	0.198
	Constant	-5.451	0.004	
PDO Collisions[c]	$ln(AADT_{major})$	0.988	<0.001	0.034
	$ln(AADT_{minor})$	0.769	<0.001	
	$Left\ turn\ lanes_{major}$	-0.193	0.009	
	Constant	-14.657	<0.001	
Non-Fatal Injury Collisions[c]	$ln(AADT_{total})$	1.339	<0.001	0.116
	Constant	-13.139	<0.001	
Injury +Fatal Collisions[c]	$ln(AADT_{total})$	1.325	<0.001	0.119
	Constant	-12.991	<0.001	

[a] All collision severities and all impact types.

[b] All collision severities corresponding to a specific impact type.

[c] All collision impact type corresponding to a specific severity level.

Table 3: Safety effectiveness of RLCs at treated sites

Collision impact type or severity level	$N_{observed;\text{"before"}}$	$N_{observed;\text{"after"}}$	$N_{expected;\text{"after"}}$	δ	θ	95%confidence interval of θ	
						lower	upper
Total Collisions [a]	194	195.5	178.4	-17.1	↑1.09	1.08	1.11
Rear-end [b]	24	78.5	71.8	-6.7	↑1.07	1.04	1.11
Angle [b]	85.66	71.2	82.0	10.8	↓0.85	0.82	0.89
Sideswipe [b]	73.66	32.4	22.9	-9.5	↑1.39	1.27	1.51
Single Motor Vehicle [b]	9.66	10.5	9.1	-1.4	↑1.12	0.87	1.37
PDO [c]	149.33	156.3	133.0	-23.3	↑1.16	1.13	1.18
Non-Fatal Injury [c]	43.33	39.2	43.0	3.8	↓0.90	0.84	0.96
Injury+Fatal [c]	43.66	39.2	43.3	4.1	↓0.90	0.84	0.96

$N_{observed;\text{"before"}}$ = average annual observed collisions in the "before" period on treated sites.

$N_{observed;\text{"after"}}$ = average annual observed collisions in the "after" period on treated sites.

$N_{expected;\text{"after"}}$ = average annual expected collisions in the "after" period on treated sites if treatment was not implemented.

δ = percentage change in safety due to the treatment ($N_{expected;\text{"after"}}$ minus $N_{observed;\text{"after"}}$).

↑ Indicates an increase in annual collision frequency.

↓ Indicates a reduction in annual collision frequency.

4 Concluding Remarks

This paper presented a study to assess the safety impacts of RLCs at signalized intersections in the City of Ottawa, Ontario, Canada. The analysis utilized collision records for objective safety analysis using regression analysis approach and EB before-and-after study data. While the regression analysis approach of collision data on treated intersections showed that the presence of RLCs reduced angle, injury, and fatal collisions, the effect of RLCs on other impact types and severity levels was found to be insignificant. On the other hand, the EB before-and-after study showed a significant impact for RLCs, where total collisions increased by about 9% and PDO collisions increased by 16%. However, injury and injury+fatal collisions decreased by about 10%. The results also indicated that RLC increased sideswipe and rear-end collisions by about 39% and 7% while significantly reducing angle collisions by about 15%. Both regression analysis and EB approaches indicated that the presence of RLCs decreased angle, injury, and fatal crashes. These results of the EB study are in general agreement with many studies in the literature. The difference between the regression analysis and EB approaches may have resulted from the relatively small number of treated sites for which collision data were available. This small sample size could have affected the reliability of the regression analysis approach. In summary, the results of this study suggest that RLCs at signalized intersections reduced severe collisions involving injury or fatality while increasing PDO collisions.

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