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Evaluation and spatial analysis of automated red-light running enforcement cameras

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ABSTRACT

Red light cameras may have a demonstrable impact on reducing the frequency of red light running violations; however, their effect on the overall safety at intersections is still up for debate. This paper examined the safety impacts of Red Light Cameras (RLCs) on traffic crashes at signalized intersections using the Empirical Bayes (EB) method. Data were obtained from the Florida Department of Transportation for twenty-five RLC equipped intersections in Orange County, Florida. Additional fifty intersections that remained with no photo enforcement in the vicinity of the treated sites were collected to examine the spillover effects on the same corridors. The safety evaluation was performed at three main levels; only target approaches where RLCs were installed, all approaches on RLC intersections, and non-RLC intersections located on the same travel corridors as the camera equipped intersections. Moreover, the spatial spillover effects of RLCs were also examined on an aggregate level to evaluate the safety impacts on driver behavior at a regional scale. The results from this study indicated that there was a consistent significant reduction in angle and left-turn crashes and a significant increase in rear-end crashes on target approaches, in addition, the magnitude and the direction of these effects, to a lesser degree, were found similar on the whole intersection. Similar trends in shift of crash types were spilled-over to non-RLC intersections in the proximity of the treated sites. On an aggregate county level, there was a moderate spillover benefits with a notable crash migration to the boundary of the county.

1. Introduction

According to the Insurance Institute for Highway Safety (IIHS, 2013a, b), nearly 2 million crashes annually occur at intersections. In 2011, red-light running resulted in 714 fatalities and an estimated 144,000 injuries in the United States (IIHS, 2013a, b). Red light running is a significant traffic violation, a study conducted by Hill and Lindly (2003), on red light violation from 19 intersections in four states; they found that the violation rates averaged 3.2 per intersection per hour. Another study concluded that violation rates averaged 3 per intersection per hour analyzing five busy intersections during several months in Fairfax City, Virginia (Retting et al., 1999a, b). Brittany et al. (2004) conducted a study on 9951 fatal crashes at traffic signals in year 1999 and 2000; they found that 20 percent of the drivers failed to obey the signals. According

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to the Federal Highway Administration (FHWA, 2013), 55.8 percent of Americans admit to running red lights while more than 95 percent of drivers fear that they will get hit by a red light runner when they enter an intersection.

In 2005, 96 people were killed and 6300 were injured in Florida by motorists who ignored traffic signals (cause of the crash would be "failed to follow the traffic light"). Based on the Florida Crash Database (FCD), it was found that red-light running is particularly relevant to urban crashes (69.89%) and the crash risk in urban area could be 25 percent higher than rural area (Yan et al., 2005).

As one of numerous possible countermeasures to address red light running and its associated crashes, Red Light Running Cameras (RLCs) have been used in a number of US cities. The safety of signalized intersections is extensively dependent on drivers' compliance with the traffic control devices. Nevertheless, many drivers intentionally and non-intentionally violate red lights, and hence increase the risk of involvement in a crash. The main goal of photo enforcement is to change drivers' behavior on obeying the red light at intersections. Automated red light enforcement cameras have been shown to substantially reduce red light violations by photographing vehicles whose drivers run red lights. The main idea of the automated red light camera is the continuous monitoring of the traffic flow and the traffic signal. The camera will be triggered to capture the vehicle's license plate by any vehicle passing over the sensors beyond the stop line and a specified time after the signal has turned red.

Red light running is a common traffic violation resulting in an average of 750 fatalities annually and more than 260,000 injuries every year (Retting et al., 2002). Evaluating the safety effectiveness of photo enforcement programs is undisputedly important. What seems to be still in dispute is whether or not red light cameras have an effect on driver behavior on local and global sites. Running the red light resulting from minor infractions (caught in the dilemma zone) mostly occur in the first 1 s after the onset of the red which may not necessarily impose major safety concerns, nevertheless running the red-light intentionally by a reckless driver $1_{1/2}$ seconds or longer after the light turned red might be deadly (McCartt and Hu, 2013).

Retting et al., (1999a, b), reported 40 percent decrease in red light violations during the first year of camera enforcement in both Oxnard, California and Fairfax, Virginia. They found that reduction in red light violations in both cities were almost identical at intersections equipped and not-equipped with red light cameras. They concluded that camera enforcement programs may change drivers' behavior in general rather than just enforcing the drivers to comply with the traffic signals at RLC equipped intersections only. Also, they found that the crash reductions at signalized intersections were observed on a city-wide basis, even though cameras were installed at only 11 of 125 signalized intersections in Oxnard. The effect of red light cameras was found to be not limited to the specific intersections with cameras but also extended to other non-RLC equipped intersections within the area.

Using red light camera may decrease the frequency of left turn and angle crashes and increase the rear-end crashes at signalized intersections due to non-uniform changes in driver behavior especially at the beginning period after installation. Rocchi and Hemsing (1999) reported that the reduction in red light running related crashes ranged from 10 percent in New York City to 88 percent in Essex, United Kingdom. Red light cameras have been in use in Australia for more than 33 years, controlled studies in Melbourne, Sydney, and Victoria showed that the reduction in right-angle crashes ranged from 32 percent to 50 percent with moderate increase in rear-end crashes in Sydney and Victoria (Hillier et al., 1993; South et al., 1988).

Persaud et al. (2005) evaluated the safety impact of RLCs on a multijurisdictional level; although the detected effects were lower than previous studies, they provided statistically defendable and consistent results with those found in many previous studies using data from 7 jurisdictions, they concluded that RLCs decrease right-angle crashes and increase rear-end crashes.

Erke (2009) conducted a meta-analysis of the effects of red light cameras on crashes, the study found that analyses that have controlled for most confounding factors yielded the least favorable results. The study concluded that installation of RLCs leads to a 10% reduction in right-angle crashes and a 40% increase in rear-end crashes.

There is an ongoing debate about whether or not cameras can make dangerous intersections safer, 73 Florida law enforcement agencies claimed significant crash reduction in more than half of the agencies (Florida Highway Patrol, 2012). It is to be noted that these studies used the actual red light violation counts to provide conclusions about safety improvement, although violations may be used as a surrogate measure of safety, a reliable conclusion should be based on actual crash data.

The main objectives of this study are to evaluate the safety impact of photo-enforcement program in Orange County, and cities of Orlando and Apopka in Florida at multiple levels; target approaches only where the cameras are installed, all approaches of a RLC equipped intersection, and non-RLC equipped intersections located on the same corridors. To examine the overall regional effect on drivers, a spatial analysis was performed to evaluate the spillover and migration effects on a jurisdictional level.

The remainder of the paper consists of a description of data preparation, statistical methods, evaluation of spillover effects on intersection, corridor, and county levels, detailed results and discussion are followed by conclusion and recommendations.

1.1. Data description and preparation

Since the start of the photo enforcement program in 2007 in Florida, 38 signalized intersections were equipped with one, two, or three surveillance camera systems in Orange County. It should be noted that the installation and operation dates vary greatly among these locations, intersections with active red-light cameras and at least three year of crash data in the before and after periods were only considered in this study.

The data needs of the EB observational before–after analysis can be quite extensive, required data to perform observational before–after study are crash data, traffic volume data, and roadway characteristics data. Crash data collected by date (year), location, type, severity level, relationship to intersection (at-intersection, intersection related, not intersection related), and distance from the intersection. The traffic volume data requirement for intersections is the major and minor street entering Average Annual Daily Traffic (AADT). Detailed information was collected regarding geometric characteristics and traffic volumes (AADT) from the Roadway Characteristics Inventory (RCI) and automated traffic counter stations maintained by cities. It should be noted that the presence of RLC is one of the roadway characteristics data required at signalized intersections which is not reported in the RCI data. While the identification of RLC equipped intersections was relatively easy through Google Maps, cities and counties websites, the determination of the accurate installation and operation dates was a challenging task. In the State of Florida, the photo enforcement programs are typically operated by city police departments. The actual dates of installation and operation and the status of each camera were obtained from the corresponding city, county, or police agency. It is worth mentioning that not all identified photo enforced intersections currently have active red light cameras, intersections with terminated or inactive RLCs were removed from consideration in this analysis. In addition, Orange County officials tend to rotate and relocate RLCs from intersections that became safer to a more dangerous intersections.

There were 25 active red light camera equipped intersections from Unincorporated Orange County, and the cities of Orlando and Apopka in the State of Florida considered in this study as shown in Fig. 1. The choice of these jurisdictions was based on the availability of installation/operation dates as discussed earlier. To examine the direct spill-over effects, for each treated site, two untreated intersections were located in the upstream and downstream directions of active camera equipped intersections and where no RLC were installed over the study period. A total number of 50 non-RLC equipped intersections in the vicinity of the treated sites (located mostly on the same travel corridors) were identified that were similar to the treated sites in terms of intersection type and configuration, driver population, and traffic volume.

Crashes that occurred at the identified treated and untreated intersections were retrieved from the Crash Analysis Reporting System maintained by the Florida Department of Transportation (FDOT) (three years before the installation date, and three years in the after period). As indicated earlier that red light cameras were found to impact specific type of crashes at intersections; the presence of RLCs were found to decrease angle and left-turn crashes, and increase rear-end crashes. Therefore, these crash types were the main focus of this study and were referred to as target crashes. The total number of crashes for an intersection was collected by combining both at-intersection and influenced by intersection crashes. Instead of using the common arbitrary fixed distance of 250 feet, a manually identified safety influence areas was utilized in this study. It should be noted that the selection of fixed distance of influence area has no justified theoretical grounds in the literature. In order to have an accurate crash dataset that actually relate to red light running at signalized intersections, a careful examination of multiple random crash reports was performed. The preliminary investigation revealed that some crash cases that were recorded as intersection-related and were within very close distance (50–150 feet) of intersections are in fact not intersection-related; these crashes were related mostly to entry/exit movements to shopping areas in the vicinity

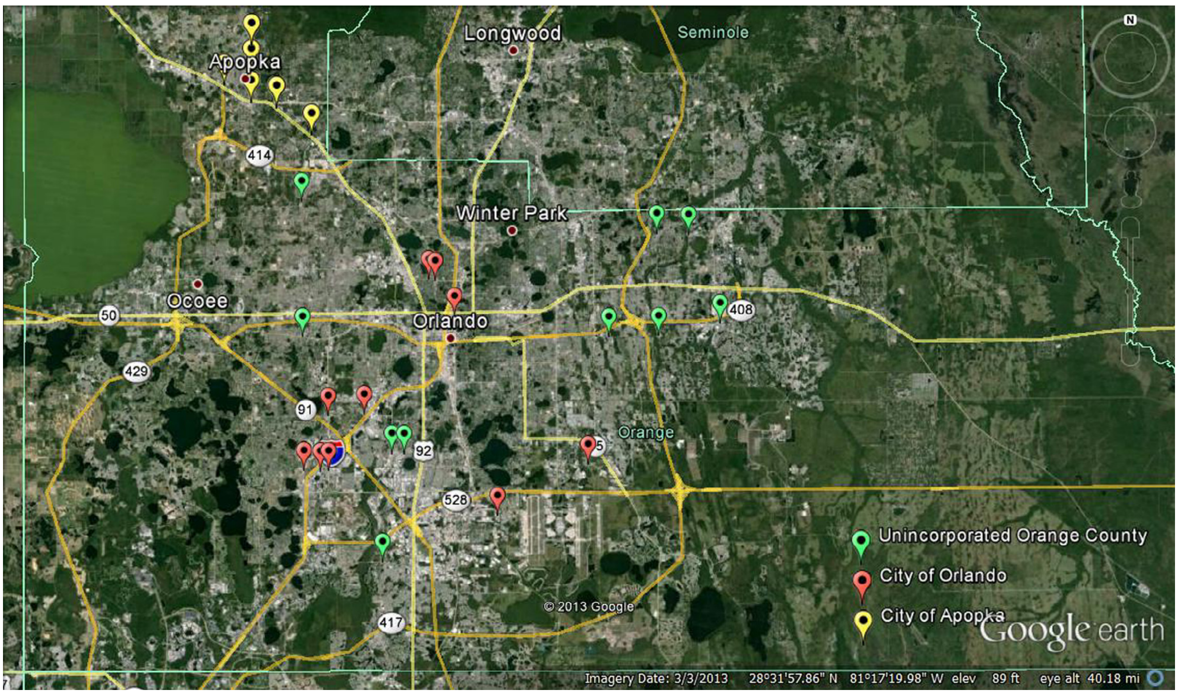

Fig. 1. Road network and geo-coded RLC intersections in Orange County – Florida.

of intersections. Therefore, angle and left-turn crashes were considered at the intersection area only (not the approaches) (Shin and Washington, 2007). While previous studies (Council et al., 2005a, b; Persaud et al., 2005) used 150 feet, another conservative study (Shin and Washington, 2007) used 100 feet for identifying RLC related rear-end crashes, in this study RLC related rear-end crashes were determined for each crash based on an extensive review of crash reports. Moreover, crashes dominated by driving under the influence of alcohol or drugs, illness, and sleep deprivation/fatigue and distraction by texting were removed from the crash dataset to examine only the effect of the presence of a RLC. Table 1 provides summary for the number of the selected RLC and non-RLC intersections and all observed crash frequencies for RLC and non-RLC intersections in all jurisdictions are summarized in Table 2.

As discussed earlier, careful considerations have been made to identify intersection-related crashes. Each intersection was analyzed by type of crash and severity level. Fig. 2 shows an example of an intersection equipped with 2 RLCs on east and west bounds (three years before and after periods) by crash type and severity level and traffic direction. It was noted that the change in frequency and severity of target crashes varied across approaches, and camera equipped intersections in the before-after periods, however, there was a notable decrease in angle and left-turn crashes and increase in rear-end crashes in terms of frequency and severity. For example, the target crash types by severity levels matrix (top-left) shows that there were total 2 angle crashes of which 1 injury and 1 PDO crash. It can be seen that there was only 1 angle crash reported as injury in the after period. The bottom part of Fig. 2 shows target crash types by directions, the locations where the RLCs are equipped are also indicated in the after period. It can be seen that the East and West bounds only were equipped with RLC, the figure also illustrates a slight reduction in rear-end crashes at the East bound while the rear end crashes were doubled at the West bound where the RLC was installed.

2. Methods

2.1. Before–after with Empirical Bayes

The accurate estimation of the safety impacts of RLCs on crashes might be challenging for various reasons; there are sundry safety related factors such as changes in traffic volume, crash reporting threshold, and the probability of reporting which are not controllable during the before-after observational periods. Moreover, installing RLCs at intersections is usually decided for safety reasons; high red light running violations and right angle crashes, etc., therefore it is necessary to account for the possible regression-to-the-mean (RTM) bias in conducting safety analyses. In such circumstances, a methodology such as the commonly used and widely accepted Empirical Bayes (EB) method should be adopted.

In the Before-After with EB method, the expected crash frequencies at the treatment sites in the 'after' period had the countermeasures not been implemented is estimated more precisely using data from the crash history of a treated site, as well as the information of what is known about the safety of reference sites with similar yearly traffic trend, physical characteristics, and land use. The EB method is based on three fundamental assumptions (Hauer, 1997); 1) the number of crashes at any site follows a Poisson distribution, 2) the means for a population of systems can be approximated by a Gamma distribution, 3) changes from year to year from sundry factors are similar for all reference sites.

One of the main advantages of the Before-After study with Empirical Bayes is that it accurately accounts for changes in crash frequencies in the 'before' and in the 'after' periods at the treatment sites that may be due to regression-to-the-mean bias. It is also a better approach than the comparison group for accounting for influences of traffic volumes and time trends on safety. The estimate of the expected crashes at treatment sites is based on a weighted average of information from treatment and reference sites as given in (Hauer, 1997):

$$\widehat{E}_i = (\gamma_i \times y_i \times n) + (1 - \gamma_i)\eta_i \tag{1}$$

Where γ_i is a weight factor estimated from the over-dispersion parameter of the negative binomial regression relationship and the expected 'before' period crash frequency for the treatment site as shown in Eq. (2):

$$\gamma_i = \frac{1}{1 + k \times y_i \times n} \tag{2}$$

Table 1
Summary of selected RLC and non-RLC intersections.

Jurisdiction	Number of intersections				
	RLC intersections				Non-RLC intersections
	All approaches	Intersections equipped with 1, 2, or 3 approaches			Number of intersections
		1	2	3	
Orange County	10	10	0	0	20
Orlando	9	4	3	2	18
Apopka	6	2	3	1	12
Total	25	16	6	3	50

Table 2
Summary of observed crashes at RLC and non-RLC sites.

Red-light cameras intersections					
Jurisdiction	Crash type	Target approaches		All approaches	
		Observed before	Observed after	Observed before	Observed after
Orange County	Angle	31	24	78	64
	Left turn	29	20	72	53
	Rear end	46	44	114	117
Orlando	Angle	28	12	85	50
	Left turn	94	67	147	134
	Rear end	96	113	197	347
Apopka	Angle	22	21	60	57
	Left turn	46	34	97	92
	Rear end	62	86	143	184
Adjacent non-red-light cameras intersections					
	Crash type	All approaches			
		Observed before		Observed after	
Orange	Angle	148		101	
	Left turn	151		132	
	Rear end	225		239	
Orlando	Angle	192		162	
	Left turn	281		243	
	Rear end	374		413	
Apopka	Angle	116		107	
	Left turn	184		172	
	Rear end	289		318	

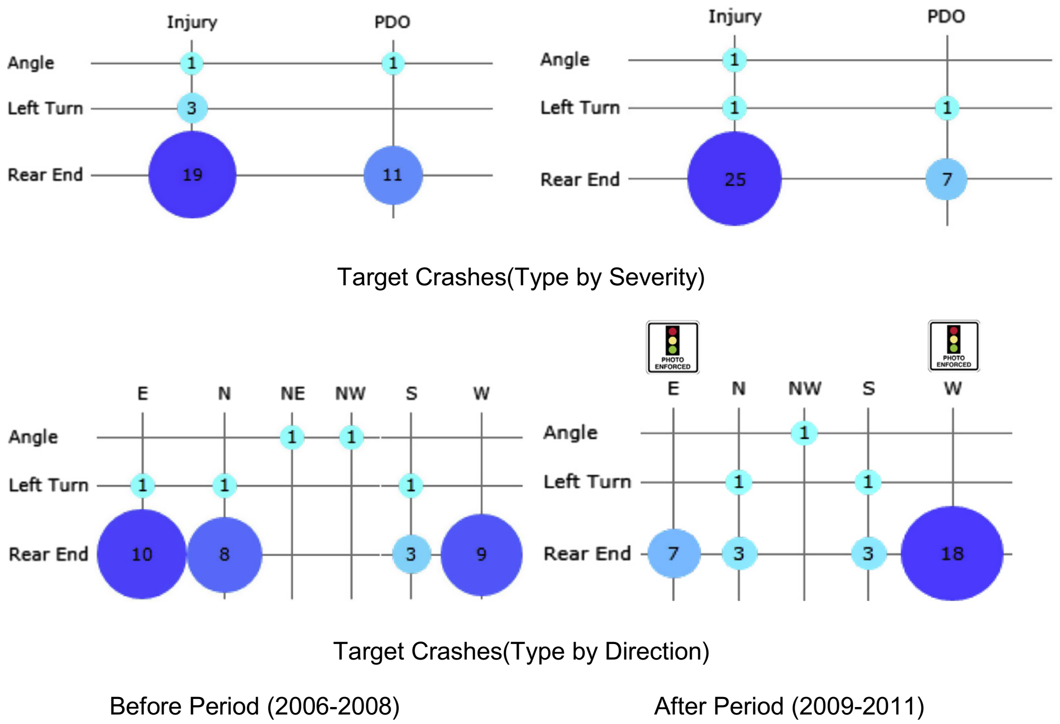

Fig. 2. Before–after target crash type by severity and direction (Conroy and Vineland intersection).

y_i = Number of average expected crashes of given type per year estimated from the SPF (represents the 'evidence' from the reference sites), η_i = Observed number of crashes at the treatment site during the 'before' period, n = Number of years in the before period, and k = Over-dispersion parameter

The 'evidence' from the reference sites is obtained as output from the SPF. SPF is a regression model which provides an estimate of crash occurrences on a given roadway intersection. Crash frequency on signalized intersections may be estimated using negative binomial regression models (Abdel-Aty and Radwan, 2000; Persaud, 1990), and therefore it is the form of the SPFs for negative binomial model fitted using crash data of signalized intersections with their geometric and traffic parameters in Florida. A typical SPF will be of the following form:

$$y_i = e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n)} \tag{3}$$

Where β_i's = Regression Parameters, x_1 and x_2 here are logarithmic values of AADT entering an intersection (Major and Minor traffic volumes), and x_i 's $(i > 2)$ = other traffic and geometric parameters of interest.

Over-dispersion parameter, denoted by k is the parameter which determines how widely the crash frequencies are dispersed around the mean.

And the standard deviation (σ_i) for the estimate in Eq. (1) is given by:

$$\hat{\sigma}_i = \sqrt{(1-\gamma_i)\times \widehat{E}_i} \tag{4}$$

It should be noted that the estimates obtained from Eq. (1) are the estimates for number of crashes in the before period. Since, it is required to get the estimated number of crashes at the treatment site in the after period; the estimates obtained from Eq. (1) are to be adjusted for traffic volume changes and different before and after periods (Hauer, 1997). The adjustment factors for which are given as below:

Adjustment for AADT (ρ_{AADT}):

$$\rho_{AADT} = \frac{AADT_{after}^{\alpha_1}}{AADT_{before}^{\alpha_1}} \tag{5}$$

Where, $AADT_{after}$ = AADT entering an intersection in the after period at the treatment site, $AADT_{before}$ = AADT entering an intersection in the before period at the treatment site, and α_1 = Regression coefficient of AADT from the SPF.

Adjustment for different before-after periods (ρ_{time}):

$$\rho_{time} = \frac{m}{n} \tag{6}$$

Where, m = Number of years in the after period, and n = Number of years in the before period.

Final estimated number of crashes at the treatment location in the after period ($\hat{\pi}_i$) after adjusting for traffic volume changes and different time periods is given by:

$$\hat{\pi}_i = \widehat{E}_i \times \rho_{AADT} \times \rho_{time} \tag{7}$$

The index of effectiveness (θ_i) of the treatment is given by:

$$\hat{\theta}_i = \frac{\hat{\lambda}_i/\hat{\pi}_i}{1+(\hat{\sigma}_i^2/\hat{\pi}_i^2)} \tag{8}$$

Where, $\hat{\lambda}_i$ = Observed number of crashes at the treatment site during the after period.

The percentage reduction (τ_i) in crashes of particular type at each site i is given by:

$$\hat{\tau}_i = (1-\hat{\theta}_i)\times 100\% \tag{9}$$

The Crash Reduction Factor (CRF) or the safety effectiveness ($\hat{\theta}$) of the treatment averaged over all sites would be given by (Persaud et al., 2004):

$$\hat{\theta} = \frac{\sum_{i=1}^{m}\hat{\lambda}_i \Big/ \sum_{i=1}^{m}\hat{\pi}_i}{1+\left(\mathrm{var}\left(\sum_{i=1}^{m}\hat{\pi}_i\right)\Big/\left(\sum_{i=1}^{m}\hat{\pi}_i\right)^2\right)} \tag{10}$$

Where, m = total number of treated sites, and based on Hauer (1997):

$$\mathrm{var}\left(\sum_{i=1}^{k}\hat{\pi}_i\right) = \sum_{i=1}^{k}\rho_{AADT}^2\times\rho_{time}^2\times \mathrm{var}(\hat{E}_i) \tag{11}$$

The standard deviation ($\hat{\sigma}$) of the overall effectiveness can be estimated using information on the variance of the estimated and observed crashes, which is given by Eq. (12).

$$\hat{\sigma} = \sqrt{\frac{\theta^2\left[\left(\mathrm{var}\left(\sum_{i=1}^{k}\hat{\pi}_i\right)\Big/\left(\sum_{i=1}^{k}\hat{\pi}_i\right)^2\right)+\left(\mathrm{var}\left(\sum_{i=1}^{k}\hat{\lambda}_i\right)\Big/\left(\sum_{i=1}^{k}\hat{\lambda}_i\right)^2\right)\right]}{\left[1+\left(\mathrm{var}\left(\sum_{i=1}^{k}\hat{\pi}_i\right)\Big/\left(\sum_{i=1}^{k}\hat{\pi}_i\right)^2\right)\right]^2}} \tag{12}$$

$$\text{Where, } \mathrm{var}\left(\sum_{i=1}^{k}\hat{\lambda}_i\right) = \sum_{i=1}^{k}\lambda_i \tag{13}$$

Eq. (1) is used in the analysis to estimate the expected number of crashes in the after period at the treatment sites, and then the values are compared with the observed number of crashes at the treatment sites in the after period to get the percentage reduction in number of crashes resulting from the treatment. The conditional binomial test and the normal approximate test using logarithm transformation of Poisson means' ratio were used to test whether or not the estimated effects are statistically significant (Hauer, 1996; Ng and Tang, 2005). The EB method requires Safety Performance Functions (SPFs) calibrated for similar reference sites (signalized 3-leg and 4-leg intersections in Florida). Florida-Specific Safety Performance Functions (SPFs) developed by the FDOT shown in Table 3 were used for total and fatal and injury crashes, these SPFs were calibrated to match Florida-Specific conditions using crash and traffic data for more than 950 signalized intersections from the whole state (Lu, 2013). Due to lack of SPFs for specific crash types for Florida conditions, the AASHTO Highway Safety Manual (2010) procedure was followed using crash proportions for target right-angle and rear-end crashes at intersections. The proportion of intersection-related right-angle crashes and rear-end crashes were estimated from the crash data of Orange County. The angle and left-turn crashes combined represent about 30% of total crashes while rear-end crashes represent about 42% of total crashes.

3. Results and discussion

The observational Before-After EB method was applied on the 25 RLC intersections. The aggregate safety effectiveness over all RLC intersections was estimated and the Poisson test of significance was performed on all target approaches and all approaches combined. As shown in Table 4, in general there was a reduction in angle and left-turn crashes, the reduction seemed to be more significant on target approaches than for all approaches for the treated sites. Angle and left-turn crashes are decreased by 24% and 26% for target approaches for all severity and Fatal and Injury (F + I) levels, respectively. Rear-end crashes for target approach are increased by 32% and 41% for all severity and F + I, respectively. The magnitude and the direction of reduction or increase in each crash type and severity level, to a lesser degree, were similar to those on target approaches, indicating spillover benefits that driver behavior might be affected on all approaches. As indicated earlier, to examine the spillover effects on adjacent non-RLC intersections, the EB method was applied on the 50 untreated intersections. The before-after periods for these intersections were demarcated by the first RLC installation date in Orange County. The results from this analysis indicated that there was a statistically significant spillover effect on adjacent intersections for angle and left-turn crashes and a no effect to a marginally insignificant effect on rear-end crashes at all and F + I severity levels, respectively.

3.1. Macroscopic GIS analysis for red-light cameras safety impacts on jurisdictional level

RLCs were found to change drivers' behavior in dealing with yellow time and red-light dilemma zone in general and therefore RLCs effects might spillover to adjacent non-RLC intersections or sometime throughout the whole jurisdiction due to drivers' sensitivity to the possibility of the presence of red light cameras at other intersections (Persaud et al., 2005; Shin and Washington, 2007). A primary feature driving many methods of spatial analysis is described by Tobler's "First Law of Geography"; "Everything is related to everything else, but near things are more related than far things" (Tobler, 1970). Crash migration is another safety countermeasure accompanying phenomena; crashes might migrate from the treated sites

Table 3
Florida-Specific SPFs for Urban Signalized Intersections (Lu, 2013).

Intersection type	Crash type/severity	Florida-specific SPFs			
		Intercept	$\mathrm{Log(AADT_{maj})}$	$\mathrm{Log(AADT_{min})}$	Dispersion (k)
3-Leg	Total	−9.589	0.725	0.453	0.404
	F + I	−8.354	0.605	0.360	0.310
4-Leg	Total	−8.877	0.740	0.404	0.457
	F + I	−9.104	0.674	0.408	0.349

Table 4
Safety effectiveness of red light cameras at urban intersections.

Approach	Severity	Angle and left-turn		Rear-end	
		CMF (Safety effectiveness)	S.E.	CMF (Safety effectiveness)	S.E
Red-light cameras intersections					
Target approaches	All severity	0.76 * (24.15%)	0.05 (5.34%)	1.32* (−32.47%)	0.08 (7.92%)
	F + I	0.74 ** (25.81%)	0.08 (7.71%)	1.41** (−40.88%)	0.1 (9.75%)
All approaches	All severity	0.84 * (15.73%)	0.04 (4.02%)	1.17** (−17.36%)	0.07 (7.11%)
	F + I	0.87 ** (13.38%)	0.09 (9.15%)	1.23 (−23.44%)	0.09 (8.92%)
Adjacent non-red-light cameras intersections					
All approaches	All severity	0.89 ** (11.25%)	0.08 (8.04%)	0.99 (1.01%)	0.12 (11.61%)
	F + I	0.92 *** (7.87%)	0.09 (8.96%)	1.08 (−8.23%)	0.1 (9.67%)

Asterisks *,**, and *** correspond with statistical significance levels at the 95%, 90%, and 80%, respectively.

to untreated sites because of possible shift in travel patterns to avoid RLC locations. This section examines crash spillover and migration phenomena at the county level using before-after cluster analysis and Kernel Density Estimation (KDE) method.

Mapping the locations of RLC equipped intersections in Orange County in Florida (cities of Orlando and Apopka, and Alafaya and Oak Ridge Census-Designated Places), it can be seen that these cameras are located close to each other forming a clusters on mostly state, county, and US roadways as shown previously in Fig. 1.

Only target crashes (angle, left-turn, and rear-end crashes) with three years of crash data (2006–2008) for the before period and three years of crash data (2010 to 2012) were considered in this analysis (the decision of selecting these years was based on the assumption that the RLC program had started in 2007 and first installation was in late 2008). Crash data were extracted for only intersection or intersection-related, no alcohol/ drugs involvement, and for crashes that occurred only on county, state roadways, and US roadways.

The first step of investigating the target crashes was to examine the spatial distribution and as such the crash hotspots could be identified and focused on for further visual safety evaluation and comparison. The countywide map with frequent target crash clusters (angle and left-turn combined and rear-end crashes) was also presented for better visualization and understanding of the spatial distribution of target crashes.

The Kernel Density Estimation (KDE) (Chainey and Ratcliffe, 2005) was used to serve the purpose of clustering the crashes and identifying the hotspots and shifts in target crash patterns in before-after periods. The KDE defines the spread of risk as an area around a defined cluster in which there is an increased likelihood of a crash to occur based on spatial dependency. It places a symmetrical surface over each point and then evaluating the distance from the point to a reference location based on a mathematical function and then summing the value for all the surfaces for that reference location. This procedure is repeated for successive points, which allows us to place a kernel over each observation, and summing these individual kernels gives us the density estimate for the distribution of crash points (Fotheringham et al., 2000).

$$f(x,y) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{d_i}{h}\right) \tag{14}$$

where f (x, y) is the density estimate at the location (x, y); n is the number of observations, h is the bandwidth or kernel size, K is the kernel function, and d_i is the distance between the location (x, y) and the location of the i^{th} observation. The main objective of placing these kernels over the crash points is to create a smooth, continuous surface. Around each point at which the indicator is observed a circular area (the kernel) of defined bandwidth is created. This takes the value of the particular indicator at that particular point spread into it according to some appropriate function. Then it sums up all of these values at all places, including those at which no incidences of the indicator variable were recorded, gives a surface of density estimates.

The ArcGIS spatial analyst tool provides the features needed to do the cluster analysis by density estimation methods. The KDE process needs that the data-points be spatially jointed. For the points to be joined spatially, fishnet of square size cells was created using the "create fishnet" tool. The cell size (cell width and height) was selected in such a way that the area under consideration is divided into a finite number of cells that can be calculated.

Figs. 3 and 4 show the Orange countywide map with clustering output from the GIS analysis for angle and left-turn crashes and rear-end crashes. The KDE technique presents the change in pattern of target crashes in before-after, the colors represent the density of crashes per square mile area. The Geographic Information System (GIS) analysis showed that there is a considerable reduction in angle and left-turn crashes. As shown in Fig. 3, the angle and left-turn crash intensities decreased

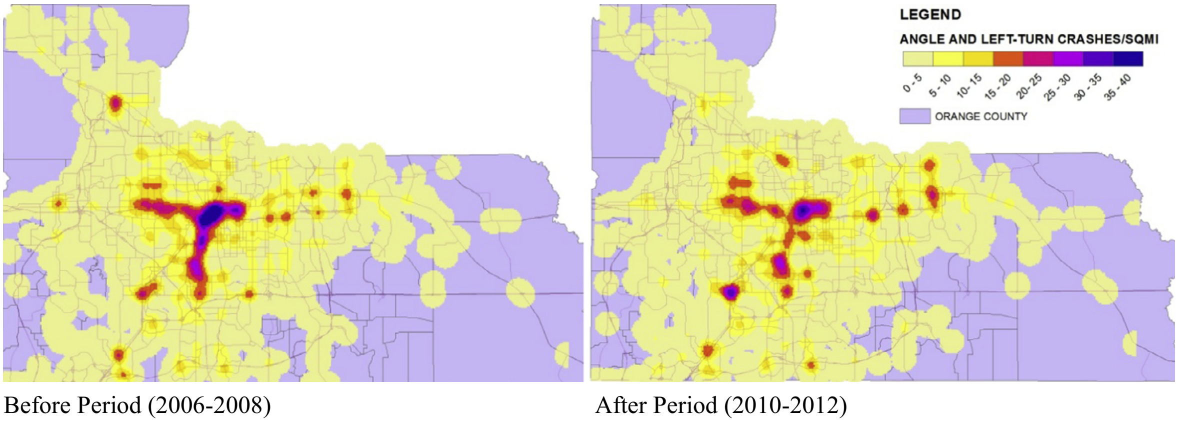

Fig. 3. Cluster before–after analysis of Angle and left-turn crashes in Orange County. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

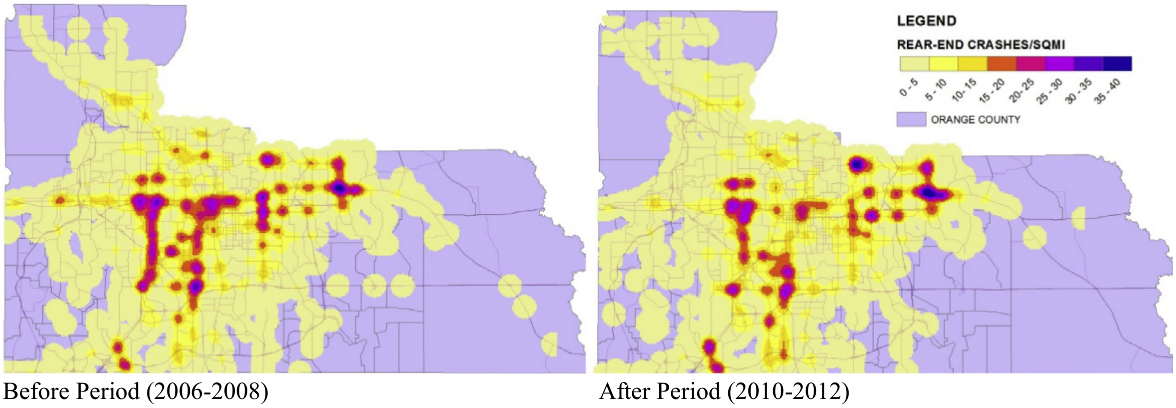

Fig. 4. Cluster before–after analysis of rear-end crashes in Orange County. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

throughout the RLC intersection clusters from 35–40 crashes per square mile to 15–20 crashes per square mile. Moreover, the areas of the affected clusters were decreased significantly.

There were a slight migration for angle and left-turn crashes, and a notable migration for rear-end crashes to the boundary of the county indicating that the spillover effects may fade away as we get farther from the RLC intersection clusters. As seen in Fig. 4, the rear-end crash clusters in red–purple-blue colors (20–40 crashes per square mile) moved from the center of the county to the east-north and south-west boundaries with greater affected area indicated by large blue spots. The analysis showed that the expected increase in rear-end crashes cannot be concluded from the generated KDE maps indicating a modest positive spillover effect. This can be explained by the assumption that drivers might be more cautious not to violate the red-light intentionally at intersections with no RLCs, while they may run the red in the first 1-s if caught in the dilemma zone to avoid a rear-end crash (violating red-light in the first second of the red is less likely to result in a right-angle crash). While it might be perceived generally that the RLC program in Florida has positively affected drivers' behavior with red-light violations in Orange County, a prospective study should be considered to account for several other factors affecting target crashes spillover and migration at signalized intersections.

4. Conclusion

The results from this study and previous research (Persaud et al., 2005; Erke, 2009; Shin and Washington, 2007; McCartt and Hu, 2013; McGee and Eccles, 2003; Council et al., 2005a, b; Washington and Shin, 2005) suggest that even though the effect of RLCs has varied widely from one intersection to another, the overall conclusion was that RLCs reduce right angle crashes and increase rear-end crashes. Consistent with prior research, Orange County's RLCs program led to significant reductions in crashes related to red light running violations (angle and left-turn crashes) at photo-enforced intersections.

Moreover, the results from this study indicated that the reduction in right-angle crashes was more significant on target approaches than for all approaches for the treated sites. Angle and left-turn crashes are decreased by 24% and 26% for target approaches at all severity and Fatal and Injury (F + I) levels, respectively (a decrease of 16% and 13% was reported for all approaches indicating a spillover effect). Rear-end crashes for target approaches were increased by 32% and 41% for all severity and F + I, respectively.

The results from this analysis indicated that there was a statistically significant spillover benefits on adjacent signalized intersections without cameras located in Orange County on the same travel corridors as the camera intersections for angle and left-turn crashes and a no effect to a marginally insignificant effect on rear-end crashes at all severity and F + I severity levels, respectively. It is worth mentioning that RLCs were found to change drivers' behavior in dealing with yellow time and red-light dilemma zone in general and therefore RLCs effects might spillover to non-RLC equipped intersections all over the jurisdiction.

In order to analyze the safety impact of RLCs program in Orange County, a GIS macroscopic analysis was performed. There was a notable reduction in frequency per square mile of angle and left-turn crashes throughout the county indicating a jurisdictional spillover benefits, the increase in rear-end crashes was not indicated by the analysis. A crash migration effects was observed in directions away and farther from clustered RLC intersections. Cluster analysis and Kernel Density Estimation could be a good tool to identify dangerous intersections with red light running problems. Moreover, the KDE cluster analysis can be used to continuously monitor the effects of different safety programs at a macroscopic level. Florida state officials tend to move red light cameras as intersections become safer, the effect of relocating RLCs needs further research. The challenge is obtaining the exact dates of termination, relocation and operation dates.

A future study might be needed to assess the impact of RLCs by using the economic cost of crashes and to improve sample sizes when installation dates become available (RLC intersections and longer before–after periods) for other counties in Florida.

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