Estimating the Safety Benefits of Red Light Cameras at Signalized Intersections in Urban Areas Case Study: The City of Virginia Beach

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Abstract

The Highway Safety Manual [HSM, 2010] recommends safety evaluations be performed before implementing any roadway treatment to predict the expected safety consequences. Safety consequences can be measured using crash prediction models, Crash Modification Factor (CMFs), or both. This paper develops a CMF to show the expected impact of red-light cameras (RLCs) on safety at signalized intersections. A CMF is a multiplicative factor used to compute the expected number of crashes after implementing a given countermeasure at a specific roadway site. RLCs are intended to improve driver's alertness to avoid causing accidents. This paper analyzes accident data reported at thirteen signalized intersections in Virginia Beach in 2008 before the RLCs were installed and 2010 after the RLCs were installed. Safety performance functions (SPFs) and the empirical Bayes (EB) before-after methodologies are used to develop a CMF for this countermeasure. The result shows an overall CMF of 0.846, which is a 15.4% safety improvement. This result is not absolute; however, but sets a starting point for further investigations and potential inclusion in the future editions of the HSM.

Keywords: Safety; crash modification factors; red-light cameras; signalized intersections; empirical Bayes

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1. Introduction

When faced with an amber light at a signalized intersection, approaching drivers are called upon to make a decision to either drive through or brake and come to a complete stop. If they are near the stop line, driving through can be necessary, but if they are far from the stop line, braking and stopping is the appropriate action. The option of what action to take becomes inconsistent when they are in the dilemma zone [Lum and Wong, 2003]. As a result, there are approximately 10 red-light running violations per hour at signalized intersections [Porter and England, 2000], a statistic significant enough to influence both safety and traffic flow at signalized intersections.

This investigation is a continuation of work by the corresponding author. It explores and measures the influence of RLCs as a countermeasure used by transportation practitioners and engineers to improve safety at signalized intersections. Placing RLCs at signalized intersections is a form of automated traffic enforcement intended to reduce the number of accidents due to red light running. This countermeasure has and continues to receive attention as an effective tool for improving safety [Martinez and Porter, 2006; and Hieatt, 2011]. In 2008, more than 2.3 million intersection-related accidents were reported in the U.S., including 7,770 fatalities and 733,000 with injuries. Of these, 762 fatalities and 165,000 injuries were due to red-light running [NHTSA, 2009]. Half of the fatalities were not the signal violators, but drivers and pedestrians hit by violators [IIHS, 2007].

The HSM [2010] recommends that safety evaluations to be performed before implementing any roadway treatment to predict the expected safety consequences. Safety consequences can be measured using crash prediction models, CMFs, or both [HSM, 2010]. This paper develops a CMF to show the impact RLCs have on safety. A CMF is a multiplicative factor used to compute the expected number of crashes after implementing a given countermeasure at a specific roadway site [HSM 2010]. A CMF of approximately 1.00 shows that the proposed or implemented treatment may have no effect on safety, while a CMF of more than 1.00 shows that the treatment could result in safety degradation and a less than 1.00 CMF indicates an expected safety benefit [Gross, Persaud and Lyon, 2010].

2. Literature Review

Most studies have shown that the most effective tool to enforce red-light running violations is installing cameras. Such countermeasures reduce injury oriented crashes by approximately 25-30% [Retting and Kyrychenko, 2002] and overall violations by approximately 40% [Retting, Ulmer and Williams, 1999]. Hieatt [2011] showed that in 2008 through 2009, the city of Virginia Beach installed RLCs at thirteen intersections to improve safety. In 2010, the total number of accidents per year at these locations had decreased by 24%. In addition to safety issues, studies such as Porter and England [2000], which analyzed actual traffic volume per light cycle data and their corresponding red-light running rates from two urban intersections, show that red-light running activities also exert pressure on traffic volumes at intersections that result in congestion.

Some studies, however have suggested that RLC installation at intersections may actually increase the number of accidents hence degrading safety. One such study was by Erke [2009] who conducted a meta-analysis on the effects of RLCs on accidents at signalized intersections. The study found that installing RLCs increased the overall number of accidents by approximately 15%. In particular, the study indicated that the rear-end accidents increased by approximately 40%, apparently because RLCs cause drivers to break abruptly and unexpectedly [Retting, Ferguson, and Hakkert, 2003]. Garber et al. [2005] also found the same trend while evaluating RLC enforcement programs in Virginia. Erke [2009] also found out that right angle accidents reduced by approximately 10%, the target crashes for RLC [Erke, 2009].

Practitioners have taken several steps to reduce red-light running activities. Traditionally, police patrols have been used to enforce red-light running. However, this approach has significant setbacks because police departments have limited resources and violators learn to avoid police [Martinez and Porter, 2006]. Violators know that enforcement is irregular, and inconsistent. For example, Porter and Berry [2001] show that police are likely to stop only two out of ten violators. Another approach taken to reduce red-light running is configuring light cycles in accordance with the Institute of Transportation Engineers (ITE) protocol that is increasing the duration times for amber and red intervals. This reduces injury associated crashes by approximately 12%, and pedestrian-bicycle crashes by approximately 37% [Retting, Chapline and Williams, 2002].

While estimating the effects of RLC enforcement on per capita fatal crash rates at signalized intersections, Hu et al. (2011) used Poisson regression distributions to compare the crash rates in 14 cities with RLCs to 48 cities without RLCs for the year 2008. The study determined that: (1) the average annual red-light running fatal crash rates reduced for both study groups, but the improvement was larger for the cities with RLC enforcement programs than for those cities without camera programs (35% vs. 14%); (2) the average annual rate of all fatal crashes at signalized intersections decreased by 14% for cities with camera programs and increased slightly (2%) for cities without cameras; and (3) the total fatal crash rates at signalized intersections during 2004–2008 for cities with camera programs were approximately 17% lower than what would have been expected without cameras. Thus, the study concluded that RLC enforcement programs significantly reduce both the rates of red light running crashes and the fatal crash rates at signalized intersections.

Previously, practitioners applied Crash Reduction Factors (CRFs) to estimate the safety benefits of certain countermeasure(s). However, the American Association of State Highway and Transportation Officials (AASHTO) in HSM [2010], advocate for the use of CMFs instead of CRFs. CMFs for before and after conditions are usually found by applying observational before and after studies, specifically comparison group studies, and EB studies. In comparison studies, sample sets are taken from untreated site(s) and compared to similar, but treated site(s). Both samples are assumed to be equal in all aspects of crash causing factors except the treatment being studied. The CMF is then found by determining the ratio of the observed number of accidents in the after period to those in the before period. The number of accidents in the before period at the treatment site(s) is multiplied by this ratio to determine the expected accidents at the treatment group had no treatment been applied. However, comparison studies have a setback; they assume that both treated and untreated sites have the same attributes and that there are no other safety mitigating factors affecting beyond the treatment. Realistically, this is difficult to achieve.

The EB methodology has been used by transportation practitioners for over 30 years in performing statistically before–after studies of the safety effect of treatments applied to transportation facilities. The EB is appropriate because of its ability to account for regression-to-the mean (RTM) and changes in traffic volumes over time at the treatment sites [Elvik, 2008]. A detailed discussion on the EB framework its relevance to the before-and-after studies are provided by Hauer [1997] and Hauer et al. [2002]. Practitioners have, therefore, generally accepted the use of this approach in specifying CMFs for use in designing countermeasures for hazardous locations on existing or proposed facilities [Persaud and Lyon, 2007].

Part of the EB process involves using SPFs to determine the predicted number of accidents for both before and after periods. The two common types of SPFs are the Poisson and negative binomial (NB) models [Elvik, 2008]. Accident data is discrete, non-negative, and sporadic. Therefore, the Poisson model is the most fitting and natural first choice for modeling [Poch and Mannering, 1996]. However, the Poisson model has a key limitation. It assumes that the variance of the dependent variable is constrained to be approximately equal to its mean. In contrast, accident and traffic data are likely to be over-dispersed hence the variance will tend to be significantly greater than the mean [Tegge, Jo and Ouyang, 2010]. In such situation, the NB is the most appropriate distribution to be used in SPF development.

3. Methodology

Theoretically, the EB is used to estimate the expected number of accidents (E_A) that would have occurred at a given treated site(s) in the after period had there not been any treatment. The safety effect of the given treatment is then compared to the treated site(s) with number of observed/actual accidents (O_B). Initially, the expected number of accidents (E_B) is estimated using two variables: the number of the observed accidents (O_B) in the ‘before’ period; and the SPF predicted number of accidents (P_B). P_B, can be from the same or similar sites, hence referred to as the reference group. The reference group is a collection of either the same or similar sites that have comparable geometric, traffic volume, and traffic flow characteristics to the treatment sites, but where the countermeasure has not been installed. The mathematical procedure in developing the CMF is presented in the flowchart in Figure 1.

STEP I:	Determine the sum of predicted accidents in the before period (P_B)
STEP II:	Determine the sum of expected accidents in the before period (E_B)
STEP III:	Determine the sum of predicted accidents in the after period (P_A)
STEP IV:	Determine the sum of expected accidents in the after period (E_A)
STEP V:	Determine the variance of the sum of expected accidents in the after period
STEP VI:	Determine the sum of observed/actual accidents in the after period (O_A)
STEP VII:	Determine the Crash Modification Factor (*CMF*)
STEP VIII:	Determine the variance of the CMF

Figure 1. Procedure for developing the crash modification factor

Both O_B and P_B are combined by using a weight (w) factor which determines their significance. Thus, E_B also referred to as the unadjusted EB estimate can be represented as follows:

$$E_B = w * P_B + (1-w)\frac{O_B}{n} \tag{1}$$

where n is the period of observation and w is the weight factor estimated as

$$w = \frac{1}{1 + k\sum_{n=1}^{N} P_n} \tag{2}$$

Where k is the over-dispersion parameter computed when the NB regression distribution, SPF is calibrated.

The estimated E_B is used in the development of CMFs as published in the Federal Highway Administration (FHWA) guide for developing CMF [Gross et al., 2010]. The development of CMF is presented in several steps. In the initial step, the expected number of accidents in the 'after' period in the treatment group that would have occurred without treatment, (E_A) is calculated as follows:

$$E_A = E_B * \left(\frac{P_A}{P_B}\right) \tag{3}$$

where E_B, and P_B are as previously defined, and P_A, is the predicted number of accidents in the 'after' period. The variance of E_A is estimated as follows:

$$var\,(E_A) = E_A * \left(\frac{P_A}{P_B}\right) * (1-w) \tag{4}$$

Finally, the CMF is approximately equal to the 'after' period accident counts divided by the E_A. It is an approximate because of a small adjustment based on E_A and with the variance expressed as follows:

$$CMF = \frac{\left(\frac{O_A}{E_A}\right)}{1 + \left(\frac{var(E_A)}{{E_A}^2}\right)} \tag{5}$$

$$var_{CMF} = CMF^2 \left[\frac{\left((1/O_A) + (varE_A/E_A^2)\right)}{\left(1 + (varE_A/E_A^2)\right)^2}\right] \tag{6}$$

Where O_A is the number of observed/actual accidents in the 'after' period for the treatment sites and E_A is as previously described.

4. Data Analysis and Result Interpretation

This study analyzes a set of thirteen signalized intersections to determine the safety effectiveness of RLCs at signalized intersections in Virginia Beach. In 2009, the city installed RLCs at the study intersections as shown in Figure 2. The goal was to reduce red-light running activities and improve safety at the intersections. The overall number of accidents in 2010 (after the installation of RLCs) was compared to those in 2008 (before the installation of RLCs). Safety improved at 10 intersections (marked in blue in Figure I) and deteriorated at three intersections (marked in red in Figure I). This result is consistent with the findings of other studies cited in the literature review. That is sometimes RLC are associated with safety degradation.

The traffic vehicle volumes and lane configurations for each of the major and minor approaches shown in Figure 1, are presented in Tables 1 and 2. In both tables, some intersections seem to have significant traffic volume differences; this could be due to change in travel patterns attributed to either construction activities or implementation of strategic growth areas. Columns three and four show both major and minor entering AADTs for 2008 and 2010 determined using PM Peak traffic volumes reported by the city of Virginia Beach. The AADT was calculated as follows:

$$AADT = DDHV * K * D \tag{7}$$

where, *DDHV* is the directional design hourly volume, *K* is the proportion of daily traffic occurring during the peak hour, and *D* is the proportion of peak hour traffic travelling in the peak direction of flow. All studied intersections are located in urban areas and are radial routes and as recommended by the HCM [2010], a K of 0.09 and a D of 0.55 are applied.

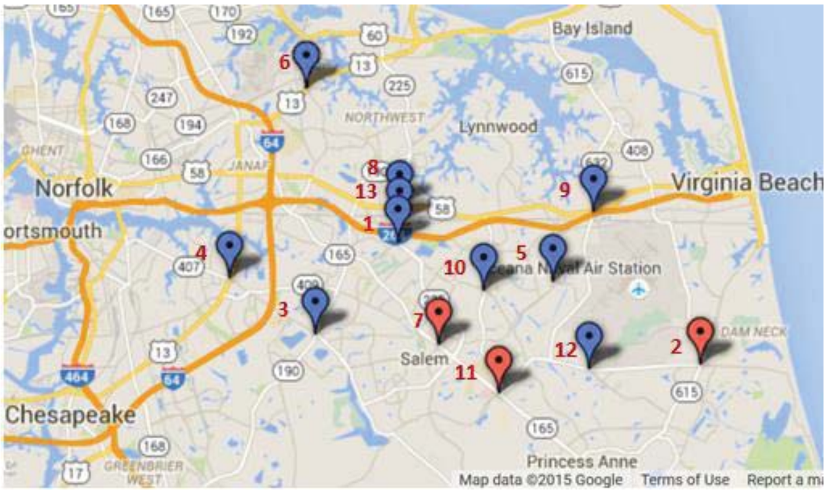

Figure 2. Study site locations

SOURCE: Google Maps and David M. Putney / The Virginian-Pilot

Table 1a. Traffic volumes and lane configurations for major approaches

		2008	2010	No. of Lanes			
	NAME	**AADT**	**AADT**	**L**	**T**	**T+R**	**R**
1	Independence Blvd.	90566	73636	1	3	0	1
2	Dam Neck Rd.	49495	47758	2	3	0	1
3	Indian River Rd.	57192	50768	2	3	0	1
4	Military Hwy.	62990	65010	1	3	0	1
5	Lynnhaven Pkwy.	33535	32384	2	2	0	1
6	Northampton Blvd.	54869	52943	2	4	0	1
7	Princess Anne Rd.	44364	45293	2	4	0	1
8	Independence Blvd.	44747	47879	2	3	1	1
9	Virginia Beach Blvd.	42549	41071	2	4	0	1
10	Holland Rd.	31980	30858	1	2	0	1
11	Princess Anne Rd.	37819	35980	2	1	1	0
12	Dam Neck Rd.	38307	37556	1	2	0	1
13	Independence Blvd.	64102	59354	2	4	0	1

Table 1b. Traffic volumes and lane configurations for minor approaches

	NAME	2008 AADT	2010 AADT	No. of Lanes L	T	T+R	R
1	Baxter Rd.	25374	25273	3	1	0	1
2	General Booth Blvd.	28949	27318	2	3	0	1
3	Kempsville Rd.	35515	30040	2	2	0	1
4	Indian River Rd.	33939	30566	2	1	1	1
5	International pkwy.	20505	19293	2	1	0	1
6	Diamond Springs Rd.	20889	19712	2	3	0	1
7	Lynnhaven Pkwy.	28404	26727	2	2	0	2
8	Virginia Beach Blvd.	37071	38465	2	4	0	1
9	Great Neck Rd.	37632	35354	1	2	0	1
10	Rosemont Rd.	27818	26251	1	2	0	1
11	Dam Neck Rd.	38089	34869	2	4	0	1
12	London Bridge Rd.	30565	28566	1	0	1	1
13	Bonney Rd.	13341	12586	2	2	0	1

As shown in Table 2, the overall number of accidents reduced from 299 in 2008 to 226 in 2010, a 24.41% reduction in crashes. Since there were no geometrical changes and no data to state otherwise, this study used the change in traffic volumes and the resulting number of accidents to be due to the RLCs implementations at the study sites. Also, presented in Table 2 are the SPF predicted numbers of accidents for each intersection.

Table 2.'Before' and 'After' period traffic volumes, observed accidents and SPF predicted accidents

	INTERSECTION	2008 Period 'Before' RLCs Installation: Actual Crashes	2008 Period 'Before' RLCs Installation: SPF Crashes	2010 Period 'After' RLCs Installation: Actual Crashes	2010 Period 'After' RLCs Installation: SPF Crashes
1	Baxter Rd. & Independence Blvd.	12	16	9	17
2	General Booth Blvd. & Dam Neck Rd.	23	20	36	18
3	Indian River Rd. & Kempsville Rd.	28	23	25	19
4	Indian River Rd. & Military Hwy.	35	22	18	19
5	Lynnhaven Pkwy. & International pkwy.	11	17	4	15
6	Northampton Blvd. & Diamond Springs Rd.	18	16	9	15
7	Princess Anne Rd. & Lynnhaven Pkwy.	22	20	27	18
8	Virginia Beach Blvd. & Independence Blvd.	30	25	15	23
9	Virginia Beach Blvd. & Great Neck Rd.	22	26	4	22
10	Holland Rd. & Rosemont Rd.	30	21	24	18
11	Princess Anne Rd. & Dam Neck Rd.	26	27	30	22
12	London Bridge Rd. & Dam Neck Rd.	23	22	14	19
13	Independence Blvd. & Bonney Rd.	19	13	11	13
	SUM OF ACCIDENTS	**299**	**268**	**226**	**239**

Table 3. Negative binomial parameter estimates for the 'before' (2008) period

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Standard Error	Lower	Upper	Wald Chi - Square	df	p-value
Intercept	2.450	0.401	1.665	3.236	37.418	1	0.000
Major road entering AADT	-4.10E-06	4.43E-06	-1.28E-05	4.56E-06	0.856	1	0.006
Minor road entering AADT	2.62E-05	9.34E-06	7.85E-06	4.45E-05	7.845	1	0.005
Dispersion	0.007	0.021	-0.034	0.048			

Dependent Variable: Number of Accidents per year

Before red light camera installation - 2008

The before period is the period before the RLCs were installed in 2008. The reported number of accidents is presented in column three. The predicted number of accidents per year is presented in columns four in Table 2. The predicted (SPF Crashes) average accidents for each intersection are estimated using the NB regression coefficients presented in Table 3.

Table 3 presents the NB regression coefficients for each of the variables along with their standard errors, Wald chi-square values, p-values and 95% confidence intervals for the coefficients. All the coefficients are statistically significant at a significance level of 0.05. The model coefficient indicate that major road entering AADT (-4.10E-06) has a decreased effect on the estimated number of accidents per year. This negative effect could be attributed to the fact that as the traffic volume increases, speed decreases and drivers become more careful due to the limited room to maneuver. The minor road entering AADT with a coefficient of 2.62E-05 has an increased effect on the estimated number of accidents per year. This positive effect could be attributed to the fact that as the traffic volume increases speed increases because drivers are not as careful due to the available room to maneuver.

Table 3 also presents the dispersion coefficient, a Poisson model is one in which this value is constrained to zero. Here, the coefficient is a positive and not zero, suggesting that the NB model form is more appropriate than the Poisson. A greater than zero suggests over-dispersion that is the variance is greater than the mean.

Using the NB coefficients in Table 3, the SPF predicted estimate for each intersection is estimated and presented in column six of Table 1 as SPF Crashes in the before period (2008) and then summed up to find the SPF predicted estimates (P_B) of 268 accidents per year.

After red light camera installation - 2010

The after period is the period after the RLCs were installed in 2010. The reported and predicted numbers of accidents per year are respectively presented in columns five and six of Table 1. The predicted (SPF Crashes) average accidents for each intersection are estimated using the NB distribution model where the resultant values are presented in Table 4.

Table 4. Negative binomial parameter estimates for the 'after' (2010) period

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi - Square	df	p-value
Intercept	2.316	1.143	0.076	4.556	4.108	1	0.043
Major road entering AADT	-5.31E-07	1.45E-05	-2.88E-05	2.78E-05	0.001	1	0.007
Minor road entering AADT	2.23E-05	2.70E-05	-3.06E-05	7.52E-05	0.682	1	0.003
Dispersion	0.272	0.018	0.107	0.307			

Dependent Variable: Number of Accidents per year

Table 4 presents the NB regression coefficients for each of the variables along with their standard errors, Wald chi-square values, p-values and 95% confidence intervals for the coefficients. All the coefficients are statistically significant at a significance level of 0.05. The model coefficient indicates that major road entering AADT (-5.31E-07) has a decreased effect on the estimated number of accidents per year. This negative effect could be attributed to the fact that as the traffic volume increases speed decreases and drivers become more careful due to the limited room to maneuver. The minor road entering AADT (2.23E-05) has an increased effect on the estimated number of accidents per year. Additionally, the dispersion coefficient is more than zero, thus, rending the NB model appropriate.

Using the NB coefficients in Table 4, the SPF predicted estimate for each intersection is estimated and presented in column 10 of Table 1 as SPF Crashes in the 'after' period (2010) and then summed up to find the SPF predicted estimates (P_A) of 239 accidents per year.

Crash modification factor – Empirical Bayes before-after

With the sum of the observed and predicted accidents in both the before (2008) and after (2010) periods determined as presented in Table 1, the EB studies are used to estimate the resultant CMF as discussed in the Methodology section and presented in Table 5.

Table 5. Crash modification factor for red light cameras at signalized intersections

Parameter	**Value**
k	0.272
w	0.015
□□	298.534
□□/□□	0.892
□□	266.167
□□□ (□□)	233.716
CMF	**0.846**
□□□ (□□□)	0.005
□□□ □□□□□ (□□□)	0.074
*95% Confidence is 0.846 ± 1.645*0.0.074*	0.701 to 0.992

Table 5 also presents E_B, the ratio of the 'after' period SPF estimates to the 'before' period SPF estimates(□□/□□), E_A and its variance. These values are used to estimate the CMF. The CMF variance and standard error are also determined to assist in CMF justification or certainty check as presented in Table 5. Taking the square root of the variance, the standard error of the CMF is 0.074. At 95% confidence level, the resulting CMF is significant and acceptable since the upper value is less than 1.0. A less than one CMF value shows improvement in safety, a CMF value that is approximately 1shows no effect on safety, and a larger than one value shows degradation in safety. More observations or a larger sample size is required to detect the same RLC impact with 95 % certainty. Therefore, it can be interpreted that installation of RLCs in urban areas can reduce the annual numbers of accidents by approximately 15.4% [(1-0.846)*100].

5. Discussion and Conclusions

The results found by this study show that RLC installations at intersections may have a significant and measurable impact on safety. Specifically, this study shows that installation of RLCs at intersections, may improve safety by approximately 15.4%.

The models presented are specific and have been tested and used before. Therefore, appropriate for this study. The findings of this study may not apply at other signalized intersections, such as those located in rural areas, the same concept can be applied. To achieve a more precise outcome, this study suggests that; (1) the number of observations be increased; and (2) as the technology for collecting traffic and crash data becomes more familiar and improved, appropriate SPFs and CMFs can be developed and included in future editions of the HSM.

Improved knowledge on this topic could lead to efficient traffic planning and control of present and future transportation facilities hence improving safety. In addition, this could lead to (1) better understanding of what facilities and conditions that are safer for drivers, (2) identification of other variables that might influence roadway safety such as road surface condition, human and weather features, and (3) better understanding of the already identified variables. Thus, continuing to design and maintaining safer transportation facilities.

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