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The impact of red light cameras on safety in Arizona

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Abstract

Red light cameras (RLCs) have been used in a number of US cities to yield a demonstrable reduction in red light violations; however, evaluating their impact on safety (crashes) has been relatively more difficult. Accurately estimating the safety impacts of RLCs is challenging for several reasons. First, many safety related factors are uncontrolled and/or confounded during the periods of observation. Second, "spillover" effects caused by drivers reacting to non-RLC equipped intersections and approaches can make the selection of comparison sites difficult. Third, sites selected for RLC installation may not be selected randomly, and as a result may suffer from the regression to the mean bias. Finally, crash severity and resulting costs need to be considered in order to fully understand the safety impacts of RLCs.

Recognizing these challenges, a study was conducted to estimate the safety impacts of RLCs on traffic crashes at signalized intersections in the cities of Phoenix and Scottsdale, Arizona. Twenty-four RLC equipped intersections in both cities are examined in detail and conclusions are drawn. Four different evaluation methodologies were employed to cope with the technical challenges described in this paper and to assess the sensitivity of results based on analytical assumptions. The evaluation results indicated that both Phoenix and Scottsdale are operating cost-effective installations of RLCs: however, the variability in RLC effectiveness within jurisdictions is larger in Phoenix. Consistent with findings in other regions, angle and left-turn crashes are reduced in general, while rear-end crashes tend to increase as a result of RLCs.

Keywords: Red light running; Red light enforcement camera; Before-and-after study; Intersection safety

1. Introduction

During the period from 1992 to 1998, almost 6000 people (around 850 per year) died in red light running (RLR) crashes in the Unites States, and another 1.4 million (around 200,000 per year) were injured in crashes that involved red light running (McGee and Eccles, 2003). In Arizona in 2003, there were 5577 crashes related to red light running of which 5553, resulted in injury and 49 in death (AGOHS, 2003). As one of numerous possible countermeasures to address red light running and associated crashes, red light cameras (RLCs) have been used in a number of US cities. There is a fairly extensive body of literature focused on the impact of RLCs on specific types and severities of crashes. In most studies, even though the degree of impact has varied from site to site, the overall results of the evaluations suggest that RLCs have contributed to reducing the frequency of right-angle crashes and to increasing the frequency of rear-end crashes (Retting and Kyrychenko, 2002; McGee and Eccles, 2003). However, previous research conducted recently reports that the results of most studies are likely to be invalid as the result of methodological difficulties (Retting et al., 2003; Persaud et al., 2005).

Accurately estimating the safety impact of RLCs is challenging for several reasons. First, many safety related factors such as traffic volume, crash reporting threshold, the probability of reporting, and the driving population are uncontrolled during the periods of observation. Second, 'spillover' effect caused by drivers reacting to non-RLC equipped intersections and non-target approaches can make the selection of comparison sites difficult. Third, the sites selected for RLC installation may not be selected randomly, and as a result may suffer from the regression to the mean effect. Finally, crash severity needs to be considered to fully understand the safety impact of RLCs. With these challenges in mind, this study was designed to estimate the impact of RLCs on traffic crashes at signalized intersections in the two cities, Phoenix and Scottsdale, Arizona. More specifically, the scope and objective of the research was:

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- estimate the impact of the RLCs on safety at signalized intersection approaches equipped with cameras—referred to as target approaches;
- estimate the impact of the RLCs on safety at all signalized intersection approaches (testing for the potential spillover effect of the RLCs on non-target approaches);
- assess the sensitivity of the evaluation results from four different methodologies;
- translate the impacts estimated into economic effects.

To assess the impact of RLCs on safety, a survey was prepared that benefited from a thorough literature review and was administered to various jurisdictions in Arizona in order to obtain the necessary data and in order to determine which analysis methodologies could successfully be applied. Using the compiled dataset from survey responses, 4 evaluation methodologies were designed and administered at 10 intersections in the city of Phoenix and 14 in the city of Scottsdale, in which the installation of RLCs was determined by observed high crash frequencies, even though citywide coverage or geographic conditions for hardware installation were also considered. Our methodologies consisted of: (1) a simple before-and-after study, (2) a before-and-after study with traffic flow corrections, (3) a before-and-after study with a comparison group, and (4) an empirical Bayesian analysis to correct for potential regression to the mean effects. Applying the four analysis methods enabled us to produce a comparison of the sensitivity of the results from the different analytical assumptions and to reveal possible inconsistencies across them.

The remainder of the paper consists of a description of the target crashes as well as the before and after study methodologies. Then, additional considerations such as the spillover effect, statistical tests, and approach for quantifying economic impact are described. To conclude the paper, detailed results of the evaluation are followed by discussion and recommendations.

2. Before and after study methodologies

The analysis approach developed and described here is an expansion and mathematical formalization of the methods described by Hauer (Hauer, 1997; Hauer et al., 2002). It consists of four steps, the first being the estimation of π and λ by using various methodologies. The second step is to estimate the variance of these two estimates. The third step is to estimate the impact of treatment represented as δ and θ. The final step is to estimate the variance of the impacts. The key notations used are:

- π: expected number of crashes in the after period if the treatment had not been installed;
- λ: expected number of crashes in the after period with the treatment in place;
- $\delta = \pi - \lambda$: change in safety due to the treatment;
- $\theta = \lambda/\pi$: index of the effectiveness of the treatment.

If either δ is greater than 1 or θ is less than 1, then one concludes that the treatment is effective. The parameters π, λ, δ, and θ are unknown parameters and must be estimated using the available data. There are numerous arduous aspects of estimating these unknown parameters. Generally, the value of λ is being estimated using the observed number of crashes in the after period. It might seem that the observed number of crashes in the before period would be employed to predict the value of π. However, it is insufficient to predict the value of π using the observed number of crashes in the before period. Problems may arise in either many potential recognizable and unrecognizable factors, which may have changed from the before to after periods, or in the regression to the mean bias that has resulted from sites being selected based on prior crash histories. Thus, often more rigorous evaluation methodologies are needed to obtain accurate estimates of π, which are described in detail in the following section. Regardless of the corrections made to the before and after study, a basic four-step procedure is used (with modifications) to estimate the safety effect of a treatment.

2.1. Preliminaries: defining target crashes

Before estimating the impacts, it is necessary to define which crash types are materially affected by RLCs—referred to as target crashes. In theory, the presence of RLCs reduces the occurrence of red light running and thereby reduces the possibility of related angle and left-turn crashes. In contrast, the presence of RLCs increases the likelihood of rear-end crashes because some drivers will stop abruptly in order to avoid a potential ticket, causing the following vehicle to hit the lead vehicle. Thus, it is generally accepted that RLCs have the potential to reduce angle and left-turn crashes at signalized intersections and to increase rear-end crashes on the intersection approach on which the RLCs are installed (McGee and Eccles, 2003; Retting et al., 2003; Council et al., 2005a; Persaud et al., 2005). Therefore, crashes related to RLCs are divided into two-crash types: those attributed to RLR (i.e., angle and left-turn crashes) and those caused by actions related to avoiding RLR (i.e., rear-end crashes). Additionally, three filter criteria were used to extract target crashes from these two-crash types:

- *Distance from crash occurrence location to the center of the intersection*: Angle and left-turn crashes were extracted from the center of the intersection only. In the case of rear-end crashes, only those that occurred within 30 m (100 ft) from the center of the intersection were considered as target crashes. While a national study (Council et al., 2005a; Persaud et al., 2005) used "46 m (150 ft)" for choosing the RLC related rear-end crashes, "30 m (100 ft)" was used in this analysis—resulting in a more conservative analysis (compared to using 150 ft). Moreover, it should be noted that the selection of a static distance is justified mainly due to the ease of coding data but not on theoretical grounds. It is possible for instance that a crash 91 m (300 ft) from an intersection is intersection-related, while a crash 15 m (50 ft) from an intersection is not. These static assumptions used in a multitude of intersection safety studies are an excellent research topic in need of further study.
- *Driver's physical condition*: Crashes that involved factors such as heavy drinking, the influence of drugs, illness, and

sleep deprivation/fatigue were removed for consideration as well, as it is likely that these factors dominated the accident occurrence compared to the presence of a RLC. In addition, these factors are not directly affected by the presence of a RLC. As a result only crashes that involved drivers with “No apparent defects” were considered as target crashes.
- *Driver's prior actions*: Crashes that involved the vehicle driver's irrelevant prior actions such as entering a driveway and getting in or out of the vehicle were excluded.

All available data were used to support the study periods for the before and after RLC installation periods (Phoenix: 10/98–09/03; Scottsdale: 01/90–12/03). Lengthy evaluation periods are useful for considering regression-to-the-mean effects as well as for sample size considerations—but even under favorable conditions samples sizes can remain relatively small. The starting year of crash data for Scottsdale was adjusted from 1990 to 1991 because of the increase of the crash reporting threshold in 1991 (from US$ 500 to US$ 1000).

2.2. Estimate expected crash frequency

The first step is to estimate λ and π. The notations used to describe and develop four methodologies are:

- K (η): observed (expected) number of crashes at the treated sites in the before period;
- L (λ): observed (expected) number of crashes at the treated sites in the after period;
- M (μ): observed (expected) number of crashes at the comparison sites in the before period;
- N (ν): observed (expected) number of crashes at the comparison sites in the after period.

It is generally assumed that the expected value of λ is equal to the observed number of crashes in the after period, while the estimate of π varies across methodologies. The estimate of λ is:

$$\hat{\lambda} = L \tag{1}$$

In the following subsections, four estimation methodologies are described in detail. All estimation results and the observed crash frequencies aggregated for all RLC intersections in both jurisdictions are summarized in Table 1.

2.2.1. Simple before and after study

The simple study approach is based on the following assumptions. First, traffic volume, geometry, road user behavior, weather, and many other factors have not changed from the before to the after period. Second, there are no treatments or improvements other than the installation of RLCs in the after period. Third, the probability that the crashes are reported is the same in both periods, and the reporting threshold has not changed. These assumptions may be questionable at many sites, but it serves as a starting point for the analysis and provides results that may serve as a baseline for comparison. The predicted value of π is simply equal to the observed number of crashes in the before period: $\hat{\pi} = K$. However, the ratio for duration denoted as r_{d} (after/before period for an intersection) is used to adjust the duration difference. The modified simple predicted value of π is:

$$\hat{\pi}_{\mathrm{S}} = r_{\mathrm{d}} \cdot K \tag{2}$$

2.2.2. Before and after study with traffic flow correction

Numerous factors may influence safety, such as changes in traffic volume, geometry, signage, striping, weather, surrounding land uses, and driving populations. These factors are divided into two categories: recognizable and unrecognizable factors (Hauer, 1997). The recognizable factors are measurable and directly modeled. Traffic flow is an important recognizable factor that is extremely influential on safety and should

Table 1
Summary of observed and predicted crash frequencies for various analysis methodologies

Approach	Jurisdiction	Crash type	K[a]	L	M	N	$\hat{\pi}$			
							1[b]	2	3	4
All approaches	Phoenix	Angle	97	56	115	123	61.3	65.2	–[c]	–
		Left-turn	335	226	398	427	213.4	228.1	–	–
		Rear-end	201	162	188	199	127.5	134.7	–	–
	Scottsdale	Angle	207	113	–	–	162.6	–	160.2	135.5
		Left-turn	457	167	–	–	281.4	–	280.4	276.5
		Rear-end	676	590	–	–	397.3	–	361.6	406
Target approaches	Phoenix	Angle	50	20	–	–	32.1	34.5	–	–
		Left-turn	197	122	–	–	126.2	135	–	–
		Rear-end	81	83	–	–	51.8	55	–	–
	Scottsdale	Angle	91	62	–	–	76.8	–	73.5	76.8
		Left-turn	308	106	–	–	202.7	–	200.8	192.8
		Rear-end	199	184	–	–	116.5	–	108.7	130.4

[a] K, L, M, and N are aggregated values for all intersections in each jurisdiction (see Section 2.2).
[b] 1: Simple correction; 2: comparison group correction; 3: traffic flow correction; 4: empirical Bayesian correction.
[c] Not applicable.

be considered. Then, the estimate of π is given:

$$\hat{\pi}_{\mathrm{T}} = \hat{r}_{\mathrm{tf}} \cdot K = \frac{f(\widehat{A_{\mathrm{avg}}})}{f(\widehat{B_{\mathrm{avg}}})} \cdot K \tag{3}$$

where r_{tf} is the ratio of traffic flow in the before period to that in the after period, and $\widehat{A_{\mathrm{avg}}}$ and $\widehat{B_{\mathrm{avg}}}$ represent the expected traffic volume during the after and before periods respectively. Since the relationship between traffic flow and safety is not typically proportional, it should be represented by the safety performance function (SPF)—a functional relationship between traffic volumes and safety for a specific site or class of sites. The general approach used to develop SPFs involves the use of count based models, the most popular of which are the Poisson and negative binomial regression models (Washington et al., 2003). Thus, the SPFs using the Poisson regression model are represented:

$$E[y_i|\mathbf{x}_i] = \exp(\mathbf{x}_i'\boldsymbol{\beta}) \tag{4}$$

where y_i is the number of crashes per year at intersection i, $\mathbf{x}_i$ is a vector of AADT at intersection i, and $\boldsymbol{\beta}$ is estimable parameters. Theoretically, the expected number of crashes from the Poisson regression model is the same as that from the negative binomial regression model. However, the variances are different since the data are generally over-dispersed as shown in Eq. (5); the parameter α is commonly referred to as the over-dispersion parameter.

$$\mathrm{Var}[y_i|\mathbf{x}_i] = \exp(\mathbf{x}_i'\boldsymbol{\beta})[1 + \alpha \cdot \exp(\mathbf{x}_i'\boldsymbol{\beta})] \tag{5}$$

Due to data availability, traffic flow adjustments are considered in Scottsdale only. The SPFs estimated using the Poisson or negative binomial regression model are summarized in Table 2. Since the number of accidents is positively associated with traffic flow, and Scottsdale had some significant traffic flow decreases in recent years due to a freeway constructed in the city, the estimates of π using the traffic flow correction are less than those using the simple approach as shown in Table 1.

2.2.3. Before and after study with a comparison group

Explicitly, the before and after study with a comparison group is different from the simple before and after study (with traffic flow correction) in that it attempts to consider unobserved factors, which cannot easily be modeled. The comparison group method is a variation of the common experimental study with a control group, in which the treatment and control groups are randomly selected from the pool of potential intersections for RLC installation. However, the comparison group is selected based on its similarity to the pre-selected RLC intersections (i.e., without random selection). The key assumption for the comparison group method is that the ratio of the expected number of target crashes in both periods is the same for both the treated and comparison sites. This suggests that unobserved changes in safety, such as driving population, weather, etc., affect comparison sites in the same way as treated sites. The estimate of π is given:

$$\hat{\pi}_{\mathrm{C}} = \hat{r}_{\mathrm{T}} \cdot K = \hat{r}_{\mathrm{C}} \cdot K = \frac{N/M}{1 + 1/M} \cdot K \tag{6}$$

Table 2
Safety performance functions used in the traffic flow and EB corrections

SPF[a]	Dependent Variable (crashes)	Constant	Ln (AADT)[b]	Ln ($AADT_{maj}$)	Ln ($AADT_{min}$)	Ln ($AADT_t$)	Ln ($AADT_p$)	Number of lanes	Average yellow time (s)	Over-dispersion (α)
SPF 1	Total	−6.7553 (2.8745)	0.7486 (0.2572)							0.1767049
	Angle	−9.1274 (5.4008)				0.8814 (0.5374)				–[c]
	Left-turn	−1.2662 (2.8137)					0.2109 (0.2738)			0.6064404
	Rear-end	−18.5755 (5.3222)				1.9139 (0.5287)				0.4614633
SPF 2	Total	−7.1604 (2.0635)	0.8586 (0.1842)							0.1033756
	Angle	−2.4158 (3.6603)	0.2511 (0.3261)							–
	Left-turn	−1.1042 (3.3460)	0.2176 (0.2981)							0.4171307
	Rear-end	−19.7030 (3.7963)	1.9187 (0.3372)							0.1906724
SPF 3	Total	−9.7632 (2.2361)		0.9508 (0.2253)	0.2945 (0.1409)			−0.1008 (0.0509)		0.0706691
	Angle	−2.4157 (3.6518)	0.2511 (0.3267)							2.64E-06
	Left-turn	−1.6153 (3.3281)		0.1867 (0.4124)	0.0933 (0.2887)					0.4116516
	Rear-end	−15.1392 (7.4975)		1.4653 (0.4184)	0.7799 (0.2793)			−0.2879 (0.2089)	−0.9092 (0.9235)	0.1568783

Note: For parameter estimates, associated standard deviations are in parentheses.
[a] SPF 1: SPFs for target approaches used in the traffic flow correction and EB correction ($n = 48$); SPF 2: SPFs for all approaches used in the traffic flow correction ($n = 49$); SPF 3: SPFs for all approaches used in the EB correction ($n = 49$).
[b] AADT: AADT on all approach legs; $AADT_{maj}$: AADT on major roads; $AADT_{min}$: AADT on minor roads; $AADT_t$: AADT on target approaches; $AADT_p$: AADT on perpendicular approaches.
[c] Not applicable.

where r_T and r_C are the ratio of the after to the before expected target crashes at treated sites and comparison sites respectively (i.e., $r_T = \pi/\eta$; $r_C = \nu/\mu$), and these two ratios are identical under the comparison group method assumption. Since the ratio r_C is a random variable consisting of a non-linear combination of two random variables (μ and ν) and the observed counts of target crashes at comparison sites are Poisson distributed, the estimate of π is represented as Eq. (6) with the observed values.

The comparison group method is applied to Phoenix only because of the lack of data for comparison sites in Scottsdale. Comparison ratios (r_C) range from 1.028 to 1.162, which are estimated by using the crash data from 13 comparison sites extracted by the city of Phoenix based on their similarity to the RLC intersections in Phoenix. The estimated comparison ratios suggest that the crash frequency at comparison sites slightly increases in the after period. Therefore, the estimates of π using the comparison sites are greater than those using the simple approach as shown in Table 1.

2.2.4. Empirical Bayesian before and after study

In the previous approaches, the observed crash count in the before period (K) plays a key role in estimating π with the correction factors (i.e., r_{tf} and r_C). However, it is also necessary to consider the possible regression-to-the-mean (RTM) bias in safety studies. When sites are selected due to a high crash count history for the treatment as the installation of RLCs in Arizona, the observed crash frequency K is likely to suffer from RTM bias, and the best estimate of π is conditionally defined as $E[\kappa|K]$. In such circumstances, the observed crash K and the expected value k are thought of as a *sample* and as a *prior*, respectively in the Bayesian model. Under the assumption that the observed crash frequency (K) is Poisson distributed with parameter κ, and the prior distribution for κ is a gamma distribution with parameters a and b, the posterior density for κ is represented as Eq. (7) by the Bayesian theorem:

$$f(\kappa|K) = \frac{f(K|\kappa)\cdot f(\kappa)}{f(K)} = \frac{(a+1)^{K+b}}{\Gamma(K+b)}\cdot \kappa^{(K+b-1)}\cdot e^{-(a+1)\kappa} \tag{7}$$

where $f(\kappa|K)$ is the posterior density of parameter κ given sample K, $f(\kappa)$ is the prior density of parameter κ in which κ is considered a random variable, and $f(K|\kappa)$ is the likelihood of sample K. Then, the Bayesian expected value of κ is expressed:

$$E[\kappa|K] = w\cdot E[\kappa] + (1-w)\cdot K;\quad w = \frac{E[\kappa]}{E[\kappa]+\mathrm{Var}[\kappa]} \tag{8}$$

where the term w is a weight between 0 and 1. In Eq. (8), $E[\kappa|K]$ is interpreted as the expected count of crashes for a site given observed crash frequency K, and $E[\kappa]$ is the average crash frequency of the reference group, which is similar to the comparison group, but the reference group should have data about crashes as well as other covariates for the safety performance function used in the empirical Bayesian (EB) method. The weight w consists of the average crash frequency of similar intersections (i.e., $E[\kappa]$) and the variation around $E[\kappa]$ (i.e., $V[\kappa]$). If w is estimated to be near 1, then the $E[\kappa|K]$ of the intersection of interest is close to the mean of its reference population ($E[\kappa]$). On the contrary, if w is estimated to be near 0, then the $E[\kappa|K]$ of the intersection of interest is mainly affected by the observed crash frequency (K).

The two components $E[\kappa]$ and $V[\kappa]$ play a pivotal role in obtaining the Bayesian estimator $E[\kappa|K]$ as shown in Eq. (8). The two components are expressed using two parameters for the *prior* and are empirically estimated using observed data (Carlin and Louis, 2000). In the EB approach, it is common to assume that the crash frequency serves as data from a negative binomial distribution (Hauer, 1997; Hauer et al., 2002). By using a negative binomial regression model, the two pivotal components can be estimated:

$$\hat{E}[\kappa] = f(\text{covariates});\quad \widehat{\mathrm{Var}}[\kappa] = \hat{E}^2[\kappa]\cdot\alpha;$$
$$\hat{w} = \frac{\hat{E}[\kappa]}{\hat{E}[\kappa]+\widehat{\mathrm{Var}}[\kappa]} \tag{9}$$

where the estimate of $E[\kappa]$ and an over-dispersion parameter α are obtained by using SPFs for the EB correction shown in Table 2. Therefore, the weight w in Eq. (8) is estimated by using the estimates of $E[\kappa]$ and $V[\kappa]$, and the EB estimate of π is given by:

$$\hat{\pi}_{EB} = \hat{E}[\kappa|K] = \hat{w}\cdot\hat{E}[\kappa] + (1-\hat{w})\cdot K \tag{10}$$

Due to the lack of a complete reference group dataset, the EB correction is applied only to the city of Scottsdale by using the safety performance functions in Table 2. It should be noted that the EB estimate of π is always between K and $E[\kappa]$. In addition, $E[\kappa]$ should be less than or equal to K when treatment sites are selected by high crash frequency.

2.2.5. Sensitivity of estimates of π across methodologies

Applying four different analysis methods enables the comparison of the sensitivity of the results and the identification of the possible inconsistencies in them. Table 1 shows the results of the predictions of crashes in the after period in the absence of a RLC. In Phoenix, the predicted values obtained by using the simple approach are slightly less than those obtained by using the comparison group method. This is because the correction ratios are greater than 1, indicating that the crash frequencies were expected to increase in the after period (rather than stay constant as the simple method assumes). In Scottsdale, the average reduction in traffic flow during the after period results in the prediction to decrease compared with the simple approach. The decrease in predictions for angle and left-turn crashes obtained by using the EB correction reflects the adjustment of the RTM bias.

2.3. Estimate the impact of treatment represented as δ and θ

The next step is to estimate the impact of RLCs on safety represented as δ and θ, in which the estimators of both are a function of $\hat{\lambda}$ and $\hat{\pi}$. Eq. (11) presents the unbiased estimators for δ and θ, in which the estimator of θ was obtained by using the well-known delta approximation, because θ is a non-linear function of two random variables. Since the applications of the delta method are necessarily brief, the interested reader can refer to two references for a full derivation and justification (Hauer, 1997; Washington and Shin, 2005) and consult two of a variety of references for the delta method (Greene, 2003; Hines et al., 2003).

$$\hat{\delta} = \hat{\pi} - \hat{\lambda}; \quad \hat{\theta} \cong \frac{\hat{\lambda}/\hat{\pi}}{1 + \widehat{\mathrm{Var}}[\hat{\pi}]/\hat{\pi}^2} \tag{11}$$

Eq. (11) shows that it is also necessary to estimate the variance of $\hat{\pi}$ in order to estimate the index of the effectiveness θ. The variances for $\hat{\pi}_{\mathrm{S}}$, $\hat{\pi}_{\mathrm{T}}$, and $\hat{\pi}_{\mathrm{C}}$ are shown in Eq. (12), which are estimated using the delta method along with the assumption that the number of target crashes is Poisson distributed (often the case at a single site). However, the variance of $\hat{\pi}_{\mathrm{EB}}$ is estimated from the fact that the variance of the posterior density for κ in Eq. (7) is $(1 - w) \cdot E[\kappa|K]$. Again, a full derivation and justification for the variances of $\hat{\pi}$ can be found in Hauer (1997) and Washington and Shin (2005).

$$\begin{aligned}
\widehat{\mathrm{Var}}[\hat{\pi}_{\mathrm{S}}] &= r_{\mathrm{d}}^2 K \\
\widehat{\mathrm{Var}}[\hat{\pi}_{\mathrm{T}}] &= \hat{r}_{\mathrm{tf}}^2 \cdot K + K^2 \cdot \widehat{\mathrm{Var}}[\hat{r}_{\mathrm{tf}}] \\
\widehat{\mathrm{Var}}[\hat{\pi}_{\mathrm{C}}] &= \hat{\pi}^2 \cdot (1/K + \widehat{\mathrm{Var}}[\hat{r}_{\mathrm{C}}]/\hat{r}_{\mathrm{C}}^2) \\
\widehat{\mathrm{Var}}[\hat{\pi}_{\mathrm{EB}}] &= (1 - \hat{w}) \cdot \hat{\pi}_{\mathrm{EB}}
\end{aligned} \tag{12}$$

The final step is to estimate the variances of the effects obtained using the four different methods, which are then used to approximate the "level of confidence" of the results. Eq. (13) shows the unbiased estimators for the variances of $\hat{\delta}$ and $\hat{\theta}$, in which the variance of $\hat{\theta}$ is also obtained by using the delta method (Hauer, 1997; Washington and Shin, 2005).

$$\widehat{\mathrm{Var}}[\hat{\delta}] = \hat{\pi} + \hat{\lambda}; \quad \widehat{\mathrm{Var}}[\hat{\theta}] \cong \frac{\hat{\theta}^2 \cdot \left\{(\widehat{\mathrm{Var}}[\hat{\lambda}]/\hat{\lambda}^2) + (\widehat{\mathrm{Var}}[\hat{\pi}]/\hat{\pi}^2)\right\}}{\left\{1 + (\widehat{\mathrm{Var}}[\hat{\pi}]/\hat{\pi})\right\}^2} \tag{13}$$

2.4. Additional considerations

2.4.1. Spillover effects

Spillover effects have been defined as the effects of RLCs on safety at non-camera equipped intersections in the jurisdiction by jurisdiction-wide publicity. If cameras have an effect on driver behavior that extends beyond the RLC equipped intersections, then other intersections in the area will likely also experience a decrease in angle crashes (McGee and Eccles, 2003). Previous research suggests that there are potential spillover effects from the use of RLCs (Retting et al., 1999; McGee and Eccles, 2003; Council et al., 2005a; Persaud et al., 2005; Yaungyai and Hobeika, 2005). In order to investigate potential spillover effects, the before and after study explained in the previous section should be applied to non-camera intersections in each jurisdiction. However, it is difficult to evaluate potential spillover effects due to the multiple treatment dates for each RLC intersection. A national study involving multi-jurisdictions used the year of the very first RLC installation at treated sites as the 'start date' for comparison sites. They concluded that there were weak indications of spillover effects that point to a need for a more definitive, perhaps prospective, study of this issue (Council et al., 2005a; Persaud et al., 2005). In this study, the effects on all 4 approaches and those on target approaches (i.e., the RLC equipped approach) are separately quantified and the spillover effects are calculated by subtracting the effects on the target approach from those on all approaches. Spillover effects at non-RLC equipped intersections are not examined.

2.4.2. Statistical tests for the estimated effects

It is necessary to test as to whether or not the estimated effects $\hat{\delta}$ and $\hat{\theta}$ are statistically significant. To assess significance the conditional binomial test and the normal approximate test using logarithm transformation of Poisson means' ratio were used. Assuming that X and Y are two independent Poisson random variables with parameters π and λ, the conditional binomial test was conducted using the conditional distribution of X given $X + Y = n$, which is a binomial distribution with parameters $n = \hat{\pi} + \hat{\lambda}$ and $\rho = \pi/(\pi + \lambda)$ as shown in Eq. (14) (Przyborowski and Wilenski, 1940; Weed, 1986; Sahai and Misra, 1992; Hauer, 1996).

$$\Pr(X = \hat{\pi}|n = \hat{\pi} + \hat{\lambda}) = \frac{n!}{\hat{\pi}!(n - \hat{\pi})!}\rho^{\hat{\pi}}(1 - \rho)^{n - \hat{\pi}} \tag{14}$$

Under the null hypothesis H_0: $\delta = 0$, the parameter ρ is equal to 0.5, and p-value is computed by summing the probabilities for all values of X smaller than or equal to $\hat{\pi}$ if $\hat{\pi}$ is smaller than $\hat{\lambda}$; otherwise, by summing the probabilities for all values of X larger than the estimated $\hat{\pi}$. The statistical test results from the conditional binomial test are summarized in Table 3. Alternatively, the normal approximation test for H_0: $\theta = 1$ was also used. Under the null hypothesis, the standardized test statistic with a variance $1/\hat{\pi} + 1/\hat{\lambda}$ is approximately normally distributed with mean zero and variance one (Price and Bonett, 2000; Ng and Tang, 2005). The test results by the normal approximate test are represented in Table 4, and overall test results are discussed in the next section.

2.4.3. Economic analysis

Unlike the literature for the impacts of RLCs on crash frequencies, relatively few attempts have been made to incorporate the economic impacts (Elvik and Vaa, 2004; Council et al., 2005b). However, it is necessary to translate the changes estimated in terms of crash frequencies into economic impacts because it is unclear whether or not the increase in rear-end crash negates the reduction in angle and left-turn crashes, and RLCs are likely to affect severities as well as frequencies.

Fig. 1 reveals the percent changes in severities by crash type from the before to after periods in both jurisdictions. In order to estimate the crash frequencies by severity for the before and after periods, all crash data were categorized by crash type and the KABCO scale, where K is fatality, A is incapacitating injury, B is non-incapacitating injury, C is possible injury, and O is property damage only (PDO), and simple before-after

Table 3
Summary of estimated change in safety ($\hat{\delta} = \pi - \lambda$) by various methodologies

Approach and jurisdiction	Evaluation method	Change in safety by crash type			Change in safety by severity and crash type (crashes/year)			
		Angle	Left-turn	Rear-end	Angle and left-turn		Rear-end	
					K + A + B + C	PDO	K + A + B + C	PDO
Target approaches								
Phoenix	Simple correction	12.09 (6.38)*** [a]	4.19 (14.26)	−31.19 (10.79)***	0.68 (9.97)	7.37 (8.70)*	−4.48 (5.71)	−11.80 (6.60)**
	Comparison correction	14.46 (4.89)***	13.01 (11.24)*	−27.97 (9.35)***	3.78 (6.94)	9.94 (5.76)**	−3.73 (4.36)	−10.94 (5.31)***
Scottsdale	Simple correction	14.76 (12.37)*	96.73 (18.06)***	−67.50 (17.40)***	13.47 (13.15)***	5.50 (13.06)	−2.26 (6.47)	−7.02 (10.48)*
	Traffic flow correction	11.46 (12.18)*	94.84 (17.95)***	−75.31 (17.90)***	13.21 (12.98)***	5.25 (12.90)	−2.57 (6.85)	−7.82 (11.08)*
	EB correction	14.76 (12.37)*	86.79 (11.35)***	−53.60 (14.05)***	12.45 (8.45)***	4.54 (8.64)	−1.74 (3.55)	−5.66 (5.83)
All approaches								
Phoenix	Simple correction	5.28 (9.74)	−12.56 (19.05)	−34.52 (15.60)***	−5.80 (13.43)	1.63 (11.87)	−5.55 (8.23)	−12.77 (9.88)***
	Comparison correction	9.17 (7.79)*	2.15 (15.19)	−27.27 (12.92)**	−0.59 (9.42)	5.88 (8.13)	−4.01 (5.95)	−10.67 (7.31)*
Scottsdale	Simple correction	49.59 (17.35)***	114.41 (21.54)***	−192.75 (31.52)***	20.62 (16.01)***	10.55 (16.78)*	−2.05 (12.13)	−21.48 (18.99)***
	Traffic flow correction	47.24 (17.19)***	113.45 (21.51)***	−228.37 (34.53)***	20.57 (15.90)***	10.50 (16.67)*	−3.43 (14.38)	−24.71 (22.35)***
	EB correction	22.47 (10.87)**	109.51 (14.19)***	−184.04 (25.10)***	18.29 (6.27)***	8.09 (7.26)*	−2.75 (6.19)	−23.13 (10.30)***

Note: For parameter estimates $\hat{\delta}$, associated standard deviations are in parentheses.
[a] Asterisks ***, **, and * correspond with statistical significance at the 95%, 90%, and 80% levels, respectively.

approaches are applied. As expected, the proportion of angle and left-turn crashes is reduced in the after period, while the proportion of rear-end crashes increases. It is noteworthy that the increase in the proportion of PDO rear-end crashes is greater than the increase in the proportion of fatality and injury crashes in rear-end crashes. This finding suggests that RLCs may change the proportion of crash severities at RLC intersections. An important lesson from these comparisons reveals that examination of crash frequencies alone is not sufficient to understand the impact of RLCs. It becomes apparent through examination that the severity of crashes is affected by RLCs, and this is an important consideration in the adoption and/or implementation of such programs. Thus, the economic impacts from RLCs are calculated as follows:

$$\text{Economic benefits} = \sum_{i=1}^{t}(\hat{\delta}_i \cdot C_i) \tag{15}$$

where C_i is the average crash cost of the ith severity category ($i = \{1, \ldots, t\}$) and the estimates of δ_i are the estimated changes in safety of the ith severity category. In this economic analysis the costs of RLC programs are not considered, thus benefits such as the return on safety investments are not calculated.

Table 5 shows average crash costs for the KABCO injury scale, which were obtained from previous research (Council et al., 2005b). These crash costs are categorized by crash type as well as crash severity. Due to relatively small samples (the sample sizes of fatal (K) and serious injury crashes (A) are insufficient for obtaining reliable results) two crash cost levels are ultimately used in this study—fatality plus injury (K + A + B + C) and PDO (O). The estimated changes in safety, which are derived from the various evaluation methods, are summarized in the left side of Table 3 in terms of only crash type. It is necessary, however, to estimate the changes in safety by crash severity and not just sum totals (e.g., an estimate of PDO rear-end crashes is needed, not just total rear-end crash frequencies). In order to decompose the predicted crashes by crash type into the crashes by severity, the proportion of crashes with a certain severity for each crash type obtained from the observed data were applied. This decomposition requires the assumption that the proportion shown in Fig. 1 is likely to remain constant, even though the estimates of π for each crash type are changed by corrections such as traffic flow, comparison ratio, or empirical Bayesian estimates. The changes in safety by severity as well as crash type are summarized in the right side of Table 3, and Table 6 shows the crash benefits using Eq. (15) with approximate 95% confidence limits obtained by the unbiased standard deviation. In the next section, all of evaluation results including economic impacts are described.

3. Evaluation results

The evaluation results described here include the results of the change in safety, index of effectiveness, and crash benefits. The estimation results for Scottsdale are summarized using the EB before-and-after study, while the results of the comparison group method are used for Phoenix (the EB was not available for Phoenix and the comparison group method is an improvement

Table 4
Summary of index of effectiveness ($\hat{\theta} = \lambda/\pi$) by various methodologies

Approach	Jurisdiction	Evaluation method	Index of effectiveness by crash type		
			Angle	Left-turn	Rear-end
Target approaches	Phoenix	Simple correction	0.61 (0.16)*** [a]	0.96 (0.11)	1.58 (0.24)***
		Comparison correction	0.58 (0.13)***	0.90 (0.08)	1.51 (0.17)***
	Scottsdale	Simple correction	0.80 (0.14)*	0.52 (0.06)***	1.57 (0.18)***
		Traffic flow correction	0.83 (0.15)*	0.52 (0.06)***	1.67 (0.22)***
		EB correction	0.80 (0.14)*	0.55 (0.06)***	1.41 (0.11)***
All approaches	Phoenix	Simple correction	0.90 (0.15)	1.06 (0.09)	1.26 (0.13)***
		Comparison correction	0.86 (0.12)	0.99 (0.07)	1.20 (0.10)**
	Scottsdale	Simple correction	0.69 (0.09)***	0.59 (0.06)***	1.48 (0.10)***
		Traffic flow correction	0.70 (0.09)***	0.59 (0.06)***	1.62 (0.13)***
		EB correction	0.83 (0.08)***	0.60 (0.05)***	1.45 (0.06)***

Note: For parameter estimates $\hat{\theta}$, associated standard deviations are in parentheses.
[a] Asterisks ***, **, and * correspond with statistical significance at the 95%, 90%, and 80% levels, respectively.

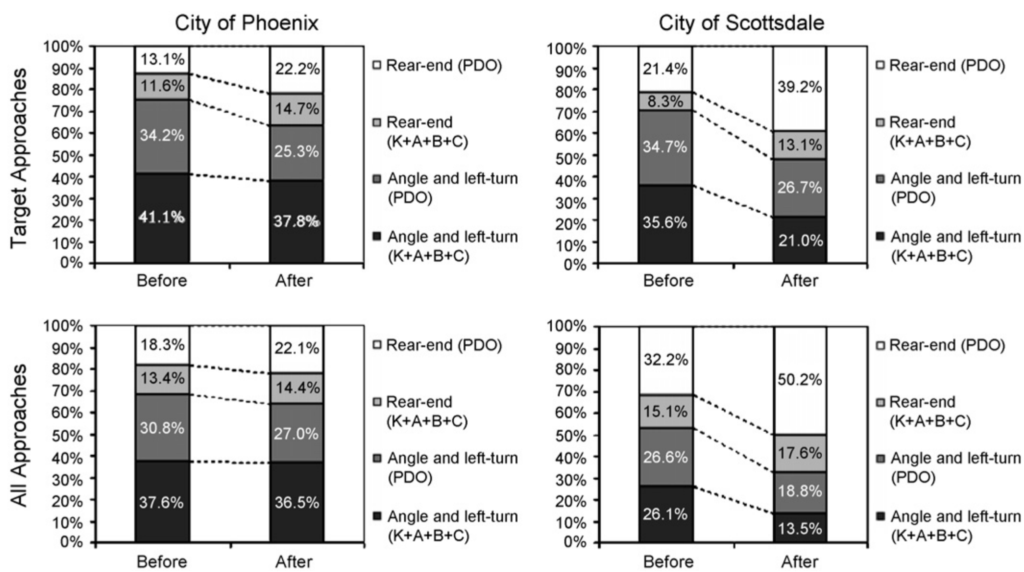

Fig. 1. Percent change in severity by crash type.

over the simple approach). As shown in Tables 3, 4, and 6, consistent with findings in other regions, in general angle crashes and left-turn crashes are reduced, while rear-end crashes increase as a result of RLCs. Estimated spillover effects and crash benefits differ across jurisdictions, although spillover effects appear to persist.

Table 5
Per-crash cost estimates by severity level

Crash severity level	Estimated crash cost (US$)	
	Angle and left turn crashes	Rear-end crashes
Fatality (K)	4,090,042	3,781,989
Incapacitating injury (A)	120,810	84,820
Non-incapacitating injury (B)	103,468	27,043
Possible injury (C)	34,690	49,746
Property damage only (O)	8,673	11,463
K + A + B + C	64,468	53,659

Source: Council et al. (2005b).

In the city of Scottsdale, angle and left-turn crashes were reduced and the rear-end crashes increased at the 14 sites with RLCs. Angle crashes for target approaches decreased by 20% (p-value = 0.105), left-turn crashes decreased by 45% (p-value < 0.000), and rear-end crashes increased by 41% (p-value = 0.001), on average. The magnitudes of reduction or increase in each crash type on target approaches are similar to those on all approaches, indicating that spillover effects are relatively high and driver behavior is affected on all approaches. The expected net safety benefit at the 14 target approaches (US$ 684,134 per year) is relatively large because the RLCs in Scottsdale contributed more to decreasing non-PDO angle and left-turn crashes than to decreasing the PDO crashes of those crash types as shown in Table 3.

In the city of Phoenix, angle and left-turn crashes were reduced and the rear-end crashes increased as a result of RLCs installed on 10 intersection approaches, as reflected by the indexes of effectiveness for various crash types in Table 4. For example, on target approaches, there was a 42% reduction in

Table 6
Crash benefits (US$/year): mean, lower, and upper 95% confidence limits

Jurisdiction and approach	Crash types	Lower (US$)	Mean (US$)	Upper (US$)
City of Scottsdale				
	Angle and left-turn	333,214	1,249,336	2,165,458
All approaches	Rear-end	−1,294,993	−412,875	469,242
	Total	−961,779	836,460	2,634,700
	Angle and left-turn	−372,941	842,135	2,057,210
Target approaches	Rear-end	−662,606	−158,001	346,604
	Total	−1,035,547	684,134	2,403,815
City of Phoenix				
	Angle and left-turn	−1,315,925	12,752	1,341,428
All approaches	Rear-end	−1,127,492	−337,588	452,315
	Total	−2,443,417	−324,836	1,793,744
	Angle and left-turn	−644,859	329,903	1,304,666
Target approaches	Rear-end	−903,058	−325,399	252,260
	Total	−1,547,917	4,504	1,556,926

angle crashes (p-value = 0.025), a marginally insignificant 10% reduction in left turn crashes at $\alpha = 0.2$ (p-value = 0.209), and a 20% increase in rear-end crashes (p-value = 0.009). The magnitudes of reduction or increase for each crash type on target approaches are greater than those on all approaches, indicating that spillover effects are relatively small. This finding may suggest that motorists in Phoenix are aware of which approaches have cameras and which do not. The expected safety net benefit, US$ 4504 per year (for 10 target approaches), is relatively small because the RLCs in Phoenix contributed more to reducing the frequency of PDO angle and left-turn crashes than to decreasing the fatalities and injuries resulting from these crashes as shown in Table 3.

The following primary conclusions are drawn from the detailed analyses of RLC data in the cities of Scottsdale and Phoenix:

- RLCs appear to reduce the frequency of angle and left-turn crashes at intersections. This reduction results from fewer drivers entering the intersection on the red indication and colliding with perpendicular traffic.
- The frequency of rear-end crashes increases at RLCs intersections, presumably due to a relatively larger number of drivers breaking suddenly to avoid a possible violation and fine.
- The severity of rear-end crashes is reduced as a result of RLCs. That is, the proportion of PDO rear-end crashes in the after period increases when compared to the before period, despite an increase in the overall frequency of rear-end crashes.
- PDO rear-end crashes consist of nearly half of all crashes after implementation of the RLC program in Scottsdale, whereas these same crashes represent less than a quarter of all crashes in Phoenix.
- Spillover effects—drivers revealing modified behavior at non-RLC approaches—appear to exist at intersections in Scottsdale, with the spillover effects nearly equal in magnitude to the target effect. In contrast, spillover effects in Phoenix are not significant.
- Examination of crash frequencies alone is not sufficient to understand the impact of RLCs. It becomes apparent through close examination that the severity of crashes is affected by RLCs, and severity thus is an important consideration in the adoption and/or implementation of such programs.
- When crash severities and costs are considered and intersections are analyzed as a system (collection of intersections), RLCs range from relatively small benefits (Phoenix) to relatively large benefits (Scottsdale).
- As is often the case in road safety studies, the variability in the effect of RLCs is large and so makes the results of statistical tests for some estimated impacts are not statistically significant. It is the reliance on other similar studies and the multi-pronged analysis approach that gives greater confidence in the mean effect.

4. Discussion and recommendations

From past research and the results of the evaluations conducted in this paper, the installation of RLCs generally reduces angle crashes and left-turn crashes, while it generally increases rear-end crashes. Although the results of the statistical tests lead to lack of statistical significance, the expected values clearly indicate consistency and agreement with prior findings (McGee and Eccles, 2003; Council et al., 2005a; Persaud et al., 2005). It is the consistency of findings across methods and agreement with past research that provides greater confidence in the expected impacts obtained in this research effort. However, all estimated impacts are not statistically significant as shown in Tables 3 and 4. Therefore, further study is needed to improve sample sizes and increase the number of crashes obtained in the sample through increased RLC intersections or longer histories. A meta analysis, as demonstrated throughout Elvik and Vaa (2004), could also be used to try and improve the precision of estimates.

One vital question has been whether or not the RLC systems in these cities, as a collection of intersections, are performing well. Much of the research has been focused on this question. Another vital concern is how well individual RLC intersections perform. That is, how much variability is there in safety performance across intersections, and how well do the "best" RLC intersections perform? RLCs may be very effective at some intersections and ineffective at others, as reported in previous research including a national study (McGee and Eccles, 2003; Persaud et al., 2005). As a consequence, it is logical to examine and contrast factors at the best and worst performing intersections. Very few factors could be examined in this investigation, and it remains a topic for future research.

To determine the suitability of an intersection for a RLC, it is necessary to examine whether the intersection is truly hazardous in terms of red light running violations and the severity of resulting crashes. An "ideal" site will have relatively high red light violation rates and will suffer from relatively severe angle and left-turn crashes. Of course the performance of intersections should be compared across similar intersections, site investigations should be performed, and crash histories examined.

It should be understood that the RLC is not a panacea to address red light running problems. In other words, the RLC is just one possible countermeasure that may be used to reduce red light running related crashes. There is comprehensive guidance available, which could be useful for jurisdictions wishing to examine current knowledge on alternative countermeasures (FHWA and NHTSA, 2003; Bonneson and Zimmerman, 2004; FHWA and NHTSA, 2005). In addition, the temporal spill-over effects need to be analyzed in order to reveal the learning process of the RLCs. Issues as to the effect of RLCs over time and driver adaptation to such systems has not been examined. Finally, a more comprehensive study is necessary to determine which crashes should be targeted for the RLC installation as well as evaluation.

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References

Arizona Governor's Office of Highway Safety, 2003. Arizona Red Light Crash Statistics. http://www.azgohs.state.az.us/redlight.html. Accessed February 21, 2007.

Bonneson, J., Zimmerman, K., 2004. Red Light Running Handbook: An Engineer's Guide to Reducing Red Light Related Crashes. FHWA-TX-05/4196-P1, Texas Department of Transportation.

Carlin, B.P., Louis, T.A., 2000. Bayes and Empirical Bayes Methods for Data Analysis. Chapman & Hall/CRC, New York.

Council, F.M., Persaud, B., Eccles, K., Lyon, C., Griffith, M.S., 2005a. Safety Evaluation of Red-light Cameras. FHWA-HRT-05-048, Federal Highway Administration.

Council, F.M., Persaud, B., Lyon, C., Eccles, K., Griffith, M., Zaloshnja, E., Miller, T., 2005b. Implementing red light camera programs: guidance from economic analysis of safety benefits. Transport. Res. Record 1922, 38–43.

Elvik, R., Vaa, T., 2004. The Handbook of Road Safety Measures. Elsevier Science, Ltd., Oxford, United Kingdom.

FHWA, NHTSA, 2003. Guidance for Using Red Light Cameras. http://www.nhtsa.dot.gov/PEOPLE/INJURY/enforce/guidance03/Guidancereport.pdf. Accessed February 21, 2007.

FHWA, NHTSA, 2005. Red Light Camera Systems Operational Guidelines. http://safety.fhwa.dot.gov/intersections/rlc_guide/index.htm. Accessed February 21, 2007.

Greene, W.H., 2003. Econometric Analysis. Prentice Hall, Upper Saddle River, New Jersey.

Hauer, E., 1996. Statistical test of difference between expected accident frequencies. Transport. Res. Record 1542, 24–29.

Hauer, E., 1997. Observational Before-after Studies in Road Safety: Estimating The Effect of Highway and Traffic Engineering Measures on Road Safety. Pergamon, Elsevier Science Ltd., Oxford, United Kingdom.

Hauer, E., Harwood, D.W., Council, F.M., Griffith, M.S., 2002. Estimating safety by the empirical Bayes method: a tutorial. Transport. Res. Record. 1784, 126–131.

Hines, W.W., Montgomery, D.C., Goldsman, D.M., Borror, C.M., 2003. Probability and Statistics in Engineering. John Wiley & Sons, New York.

McGee, H.W., Eccles, K.A., 2003. Impact of red light camera enforcement on crash experience. In: NCHRP Synthesis 310. National Research Council, Transportation Research Board, Washington, DC.

Ng, H.K.T., Tang, M.-L., 2005. Testing the equality of two Poisson means using the rate ratio. Stat. Med. 24, 965–995.

Persaud, B., Council, F.M., Lyon, C., Eccles, K., Griffith, M., 2005. Multijurisdictional safety evaluation of red light cameras. Transport. Res. Record 1922, 29–37.

Price, R.M., Bonett, D.G., 2000. Estimating the ratio of two Poisson rates. Comput. Stat. Data Anal. 34 (3), 345–356.

Przyborowski, J., Wilenski, H., 1940. Homogeneity of results in testing samples from Poisson series: with an application to testing clover seed for dodder. Biometrika 31 (3/4), 313–323.

Retting, R.A., Ferguson, S.A., Hakkert, A.S., 2003. Effects of red light cameras on violations and crashes: a review of the international literature. Traffic Inj. Prev. 4 (1), 17–23.

Retting, R.A., Kyrychenko, S.Y., 2002. Reduction in injury crashes associated with red light camera enforcement in Oxnard, California. Am. J. Public Health 92 (11), 1822–1825.

Retting, R.A., Williams, A.F., Farmer, C.M., Feldman, A.F., 1999. Evaluation of red light camera enforcement in Oxnard, California. Accid. Anal. Prev. 31 (3), 169–174.

Sahai, H., Misra, S.C., 1992. Comparing means of two Poisson distributions. Math. Sci. 17, 60–67.

Washington, S.P., Karlaftis, M.G., Mannering, F.L., 2003. Statistical and Econometric Methods for Transportation Data Analysis. Chapman & Hall/CRC.

Washington, S.P., Shin, K., 2005. The Impact of Red Light Cameras (Automated Enforcement) on Safety in Arizona. FHWA-AZ-05-550, Arizona Department of Transportation.

Weed, R.M., 1986. Revised decision criteria for before-and-after analyses. Transport. Res. Record 1068, 8–17.

Yaungyai, N., Hobeika, A., 2005. Evaluation update of red light camera program in Fairfax county, Virginia. In: Transportation Research Board 84th Annual Meeting, Washington, DC.