The Impact of Red Light Cameras (Automated Enforcement) on Safety in Arizona

Final Report 550

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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 randomly selected, 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 impacts of RLCs.

With these challenges in mind this study was designed to estimate the safety impacts of RLCs on traffic crashes at signalized intersections in the state of Arizona and to identify which factors are associated with successful installations. RLC equipped intersections in the cities of Phoenix and Scottsdale are examined in detail to draw conclusions as to the relative success of RLC programs in these two jurisdictions. Both jurisdictions are operating successful installations of RLCs. Factors related to RLC effectiveness appear to include crash type and severity, left-turn phasing, presence of warning signs, approach speeds, and signal timing. Recommendations are made as to under what conditions should RLCs be considered.</td></tr>
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SI (MODERN METRIC) CONVERSION FACTORS*

APPROXIMATE CONVERSIONS TO SI UNITS					APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	When You Know	Multiply By	To Find	Symbol	Symbol	When You Know	Multiply By	To Find	Symbol
	LENGTH					**LENGTH**			
in	inches	25.4	millimeters	mm	mm	millimeters	0.039	inches	in
ft	feet	0.305	meters	m	m	meters	3.28	feet	ft
yd	yards	0.914	meters	m	m	meters	1.09	yards	yd
mi	miles	1.61	kilometers	km	km	kilometers	0.621	miles	mi
	AREA					**AREA**			
in^2	square inches	645.2	square millimeters	mm^2	mm^2	Square millimeters	0.0016	square inches	in^2
ft^2	square feet	0.093	square meters	m^2	m^2	Square meters	10.764	square feet	ft^2
yd^2	square yards	0.836	square meters	m^2	m^2	Square meters	1.195	square yards	yd^2
ac	acres	0.405	hectares	ha	ha	hectares	2.47	acres	ac
mi^2	square miles	2.59	square kilometers	km^2	km^2	Square kilometers	0.386	square miles	mi^2
	VOLUME						**VOLUME**		
fl oz	fluid ounces	29.57	milliliters	mL	mL	milliliters	0.034	fluid ounces	fl oz
gal	gallons	3.785	liters	L	L	liters	0.264	gallons	gal
ft^3	cubic feet	0.028	cubic meters	m^3	m^3	Cubic meters	35.315	cubic feet	ft^3
yd^3	cubic yards	0.765	cubic meters	m^3	m^3	Cubic meters	1.308	cubic yards	yd^3
	NOTE: Volumes greater than 1000L shall be shown in m^3.								
	MASS					**MASS**			
oz	ounces	28.35	grams	g	g	grams	0.035	ounces	oz
lb	pounds	0.454	kilograms	kg	kg	kilograms	2.205	pounds	lb
T	short tons (2000lb)	0.907	megagrams (or “metric ton”)	mg (or “t”)	Mg	megagrams (or “metric ton”)	1.102	short tons (2000lb)	T
		TEMPERATURE (exact)					**TEMPERATURE (exact)**		
°F	Fahrenheit temperature	5(F-32)/9 or (F-32)/1.8	Celsius temperature	°C	°C	Celsius temperature	1.8C + 32	Fahrenheit temperature	°F
	ILLUMINATION						**ILLUMINATION**		
fc	foot candles	10.76	lux	lx	lx	lux	0.0929	foot-candles	fc
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2	cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
	FORCE AND PRESSURE OR STRESS					**FORCE AND PRESSURE OR STRESS**			
lbf	poundforce	4.45	newtons	N	N	newtons	0.225	poundforce	lbf
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa	kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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Glossary of Acronyms

AADT: Average Annual Daily Traffic

$AADT_{maj}$: AADT on the major road

$AADT_{min}$: AADT on the minor road

$AADT_{t}$: AADT on the target approaches

$AADT_{o}$: AADT on the opposing approaches

ADT: Average Daily Traffic

$ARLR_{c}$: AADT on the perpendicular approaches

EB: Empirical Baysian

NBRM: Negative Binomial Regression Model

RLCs: Red Light Cameras

RLR: Red Light Running

RTM bias: Regression-To-the-Mean bias

PDO accident: Property Damage Only accident

PRM: Poisson Regression Model

SPFs: Safety Performance Functions

Glossary of Notation

π: the expected number of crashes in after period if the treatment had not been installed

λ: the expected number of crashes in after period with the treatment in place

δ: change in safety due to the treatment

θ: index of effectiveness of the treatment

K: the observed number of crashes in before period at treated site

L: the observed number of crashes in after period at treated site

M: the observed number of crashes in before period at comparison site

N: the observed number of crashes in after period at comparison site

r_d: the ratio of duration

r_{tf}: the ratio of traffic flow

α: over-dispersion parameter

w: the empirical Bayesian weight

EXECUTIVE SUMMARY

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 such as traffic volumes, crash reporting thresholds, approach speeds, cycle lengths, and law enforcement practices 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 randomly selected, 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 impacts of RLCs.

With these challenges in mind, this study was designed to estimate the safety impacts of RLCs on traffic crashes at signalized intersections in the state of Arizona. More specifically, this study :

- Estimates the impact of the RLCs on safety at signalized intersection approaches equipped with cameras.
- Estimates the impact of the RLCs on safety at all signalized intersection approaches (testing for the potential spillover effect of the RLCs on non-camera equipped approaches).
- Analyzes both aggregate and disaggregate effects (RLC systems vs. intersections)
- Identifies which factors are associated with effective RLC installations.

The literature review summarizes previous research findings with regard to RLC systems and obstacles encountered in researching their effectiveness. The review also identifies engineering and behavioral countermeasures (other than RLCs) that may be used to deal with red light running (RLR) problems, and the research that has focused on estimating their relative effectiveness. Although there do exist engineering and behavioral countermeasures that reduce red light running and related crashes, a direct comparison of the safety impacts of engineering countermeasures on red light running related crashes is extremely difficult. The prime reason is that most studies on engineering countermeasures have not isolated the safety impacts of countermeasures on red light running and its consequences. Finally, the literature review identifies basic costs for installing and operating RLC systems.

A survey was administered to obtain the necessary information regarding RLC operation at signalized intersections in Arizona (see Chapter 2). Survey responses and data collected during site visits were used to develop the datasets necessary to evaluate the safety effectiveness of RLCs. Clear and concise operational definitions were needed to conduct the analysis, and are described in Chapter 3. Operational definitions include "target crashes"—those crashes affected by RLCs.

Using the dataset and the definition of target crashes, four evaluation methodologies are described and applied: a simple or naïve before-and-after study, a before-and-after study with corrections for traffic flow differences, a before-and-after study with comparison group corrections for both observed and unobserved differences across sites, and a before-and-after study with empirical Bayes' correction for regression to the mean (see Chapter 3). Applying four different analysis methods enables a comparison of the sensitivity of the results to the assumptions of the different analytical approaches and reveals possible inconsistencies in results. The various research designs apply corrections for regression-to-the-mean bias (caused by selection of RLC approaches with elevated crash frequencies) and spillover effects.

Intersections equipped with RLCs are first analyzed as a system of sites — that is, the collection of intersections in Scottsdale and the collection of intersections in Phoenix. Since intersections in these jurisdictions share common features of the RLC programs in these jurisdictions and because a collection of sites yields larger samples, this type of analysis makes sense. Then, intersections are analyzed individually, since there is potential for significant variation across intersections and because it is interesting to assess why certain RLC equipped intersections perform better than others.

Crash cost information was obtained from national cost estimates for various crash types and from categorizing crash severities at the study locations in the before and after periods. The costs of installation, operation, and maintenance of RLC systems are not considered in this analysis, and as a result costs and benefits are simply estimates of the "safety benefits" of the RLC programs. To compare the effectiveness of RLCs to alternative countermeasures would require the consideration of the costs of these systems. Through the consideration of a wide range of analysis methods and their results, the effect of RLCs on safety in the state of Arizona is assessed.

The following conclusions (described in detail in the report) were drawn from a variety of detailed statistical analyses, site visits, logical reasoning, and trend analysis:

City of Phoenix RLC Program Conclusions

The effects of RLCs on safety at intersections in Phoenix include :

1) Angle and left-turn crashes were reduced and 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. For example, on all approaches (approaches with and without cameras) there was a 14% reduction in angle crashes, essentially no change in left-turn crashes, and a 20% increase in rear-end crashes. The total number of crashes was essentially unchanged as a result of the RLCs (statistically).
2) The magnitudes of reduction or increase for each crash type on camera equipped approaches are significantly greater than those for all approaches, indicating that spillover effects are not present, on average. This finding may suggest that motorists are aware of which approaches have cameras and which do not.
3) The expected safety net benefit, $4,504 per year (for 10 target approaches), is relatively small because the RLCs in Phoenix contributed more to reducing the frequency of property-damage-only (PDO angle) and left-turn crashes than to decreasing the fatalities and injuries resulting from these crashes.
4) There is relatively large variability in the benefit from RLCs across Phoenix intersections, with several intersections that revealed a negative expected benefit. Nevertheless, the "best" performing intersections in Phoenix are similar to those in Scottsdale.

City of Scottsdale RLC Program Conclusions

The effects of RLCs on safety in Scottsdale include :

1) Angle and left-turn crashes are reduced and the rear-end crashes increase at the 14 sites with RLCs. Angle crashes for target approaches decreased by 20%, left-turn crashes decreased by 45%, and rear-end crashes increased by 41%, on average. Total crashes were slightly reduced by about 11%.
2) The magnitudes of reduction or increase in each crash type on target approaches are similar in magnitude for all approaches, indicating that spillover effects are relatively high and driver behavior is affected on all approaches.
3) The expected net safety benefit at the 14 target approaches ($684,134 per year) is relatively large because the RLCs in Scottsdale contributed more to decreasing fatal and injury angle and left-turn crashes than to decreasing the PDO crashes of those crash types.
4) There is relatively small variability in the benefit from RLCs across Scottsdale intersections, with most intersections revealing a positive expected benefit. The "best" performing intersections in Scottsdale are similar to those in Phoenix.

General System Level Conclusions

The following general conclusions are drawn from the detailed analyses of RLC data in the cities of Scottsdale and Phoenix, conducted and described in detail in this report:

1. RLCs appear to systematically 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. However, the impact on severity is different across the two cities, with crashes of these types in Scottsdale being more severe, on average, compared to Phoenix.
2. While the proportion of severe left-turn and angle crashes is reduced after installation of RLCs, the reduction was more significant in Scottsdale (35.6% to 21%) than in Phoenix (41.1% to 37.8%).
3. The frequency of rear-end crashes increases at RLC intersections, presumably due to a relatively larger number of drivers breaking suddenly to avoid a possible violation and fine.
4. The severity of rear-end crashes is reduced as a result of RLCs: the proportion of property-damage-only 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.
5. Property-damage-only rear-end crashes are 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.
6. Spillover effects — drivers modifying 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.
7. When crash severities and costs are considered and intersections are analyzed as a system (collection of intersections), the benefits of RLCs range small benefits (Phoenix) to relatively large (Scottsdale). For example, the crash costs (frequency and severity considered) of rear end crashes are slightly greater than the reduction in crash costs (benefits) for angle and left-turn crashes. In Scottsdale, in contrast, the

cost savings from reducing the severity of angle and left-turn crashes is greater than additional costs of rear-end crashes, and as a result there is an expected cost savings from the RLCs.

8. 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 this is an important consideration in the adoption and/or implementation of such programs.
9. The system level analysis results — that is comparing the Phoenix and Scottsdale RLC programs — are heavily influenced by individual intersection performance. In fact the top performing three intersections are similar in both jurisdictions, indicating that both jurisdictions have installed RLCs at intersections that have responded equally well to RLCs. Thus, the explanation of the aggregate results is that Phoenix has simply installed RLCs at more intersections where there has been little positive safety effect (increased rear-end crash costs exceed angle and left-turn crash savings).
10. As is often the case in road safety studies, the variability in the effect of RLCs is large and so makes the approximate 95% confidence intervals lead to inconclusive results. It is the reliance on other similar studies and the multi-pronged analysis approach that gives greater confidence in the mean effect.
11. As a result of 9 above, the analyses suggest that there are no statistical differences between the crash benefits across the jurisdictions. However, the effects on angle crashes and left-turn crashes are statistically different across the jurisdictions. Moreover, the results of the one-tail tests show that the effects on angle crashes in Phoenix are significantly greater than those in Scottsdale, while the effects on left-turn crashes in Phoenix are less than those in Scottsdale. In the next subsection, these differences are explained.

General Intersection Level Conclusions

The following conclusions are drawn from the detailed analyses of RLC equipped intersections analyzed as individual entities as apart from a collection of intersections. It should be noted that these results are based on small sample sizes and observed trends in the means and therefore require further research to validate. With this said, however, these results are in agreement with prior research findings.

1. The “best” performing intersections — intersections with significant positive benefits from installation of RLCs — were similar in both jurisdictions. The top three intersections in both Phoenix and Scottsdale benefited significantly from installation of RLCs, for example, and are indistinguishable from each other in terms of performance.
2. When a warning sign is installed at an intersection, the crash reduction benefits from angle and left-turn crashes appear to be greater than those at intersections without a warning sign. In contrast, the crash costs (negative benefits) from rear-end crashes are greater for intersections with a warning sign. Drivers seem to be less likely to run a red light but more likely to rear-end a lead vehicle when they are warned that a RLC is present. Nevertheless, the benefits of RLCs are likely to increase with warning signs because the crash benefits from angle and left-turn crashes for intersections are on average greater than those for intersections without a warning sign. These results are based on small sample sizes and so should be considered preliminary and inconclusive.

3. Approach speeds to intersections (as measured by posted speed limits) appear to be positively associated with the net crash benefits, as found in previous research. This is not surprising, since high speeds are associated with higher injury severities and thus RLCs may reduce severities considerably.
4. Lagging left-turn phasing appears to be associated with a relatively larger reduction in left-turn crashes, whereas leading left-turn phasing appears to be associated with a relatively larger reduction in angle crashes (through movement vehicles).

Recommendations

The following actions are recommended to maximize the impacts of RLCs and to address red light running and related crashes. The RLC is not a panacea to address red light running problems,however, it may be a promising countermeasure given the following considerations.

- It is necessary to examine whether an 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.
- Given that the conditions above are satisfied, candidate sites with high approach speeds are more likely to benefit than sites with relatively lower approach speeds, particularly for left turn crashes.
- The severity of left-turn and angle crashes at candidate sites should be examined. Left-turn related crashes are more likely to be reduced (as a result of RLCs) in the lagging phase condition, whereas angle crashes are more likely to be reduced in the leading left-turn phase condition.
- Engineering countermeasures (excluding RLCs) may be considered to deal with red light running problems (see Table 1) at candidate sites. It may be prudent to exhaust simpler and/or less costly engineering countermeasures to combat a red light running problem prior to adopting a RLC program, particular when some of the previous "ideal" conditions do not exist.
- The RLC is just one possible countermeasure that may be used to reduce red light running related crashes. Comprehensive guidance on the selection of an appropriate countermeasure is needed. The *Red-Light-Running Handbook: An Engineer's Guide to Reducing Red-Light-Related Crashes* (Bonneson and Zimmerman, 2004b), *Guidance for Using Red Light Cameras* (FHWA/NHTSA, 2003), and *Red Light Camera Systems Operational Guidelines* (FHWA/NHTSA, 2005) are useful resources for jurisdictions wishing to examine current knowledge on alternative countermeasures.
- Further study is needed to improve sample sizes, increase the number of crashes obtained in the sample (through increased RLC intersections or longer histories), and sort out some of the confounding observed between factors analyzed in this study.

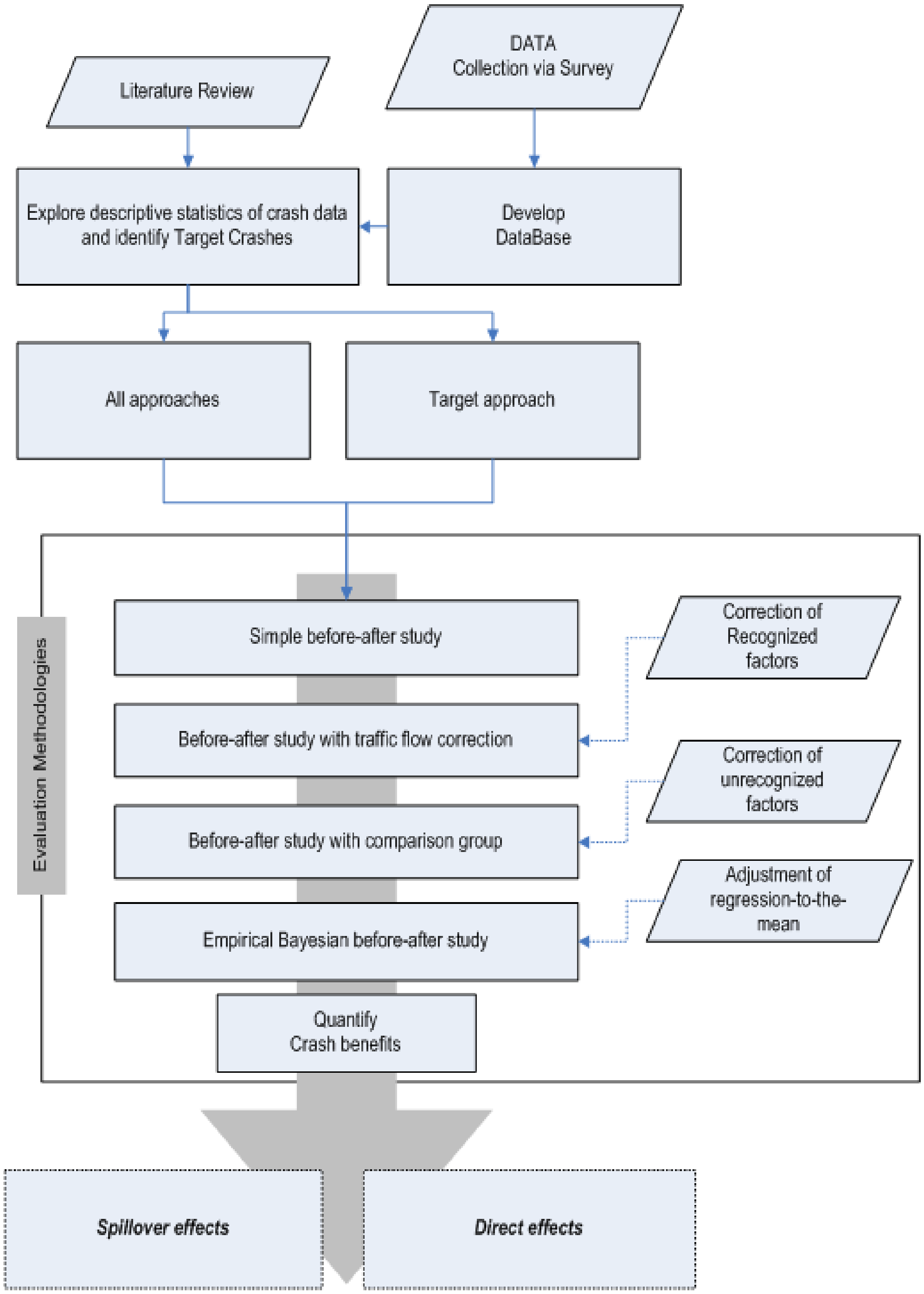

Figure 1: Flowchart of the research process

I. STUDY OBJECTIVES AND RESEARCH PROCESS

According to the Insurance Institute for Highway Safety, during the period from 1992 to 1998, almost 6,000 people (approximately 850 per year) died in red-light-running (RLR) crashes in the United States, and another 1.4 million (approximately 200,000 per year) were injured in crashes that involved red light running (McGee and Eccles, 2003). As one of numerous possible countermeasures to reduce red light running and associated crashes, red light cameras (RLCs) have been used in a number of US cities; however, careful evaluations of their effect on motor vehicle crashes and crash costs are few. In addition, the impact of RLCs has been to reduce red light violations; however, the impact on safety (crashes) is less clear. That is, the change in red light running should translate to a safety gain in the form of reduced crashes and/or crash severity. Moreover, some previous studies may have overestimated or underestimated the safety effects by disregarding regression-to-the-mean and/or spillover effects. Thus, this study is designed to consider these potential problems, and the scope of this research is to estimate the safety impact of RLC on traffic crashes at signalized intersections in the state of Arizona.

More specifically, the scope of study is to compare and contrast:

- The impact of the RLC on safety at approaches with installed cameras.
- The impact of the RLC on safety at all approaches, testing for spillover effect of the RLCs on non-camera approaches.

The overall research process of this study is shown in Figure 1. The figure shows the research steps and identifies the various methods of analysis that are employed. Initially, a survey was prepared benefiting from a thorough literature review and was administered to various jurisdictions in Arizona to obtain the necessary data and to determine which analysis methodologies could be successfully applied. In addition, which crashes are affected by RLCs — referred to as target crashes — needed to be determined. Using the compiled dataset from survey responses and the definition of target crashes, four evaluation methodologies were designed and applied: (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.

The design also considers spillover effects by separating approaches with cameras from non-camera equipped approaches. Finally, the crash benefits are estimated to examine the net benefits from the impacts of RLCs on crashes. Through the consideration of a wide range of analysis methods and their results, the effect of RLCs on safety in the state of Arizona is assessed.

II. LITERATURE REVIEW AND DATA SUMMARY

Literature Review

Red light cameras (RLCs) are not the only countermeasure available for reducing red light running and related crashes. As with many safety problems, the solution to the red light running problem may require a combination of countermeasures involving the three "E's" — education, enforcement and engineering (ITE, 2002). Generally, potential countermeasures to RLR are divided into two categories: engineering countermeasures and enforcement countermeasures (Bonneson *et al.*, 2002). In the following subsection, past research that has focused on the effects of engineering countermeasures to reduce red light running and related crashes is summarized.

The effectiveness of engineering countermeasures

Traditionally engineering countermeasures have been implemented to reduce red light running and related crashes. Many engineering countermeasures are implemented using guidelines specified in the Manual on Uniform Traffic Control Devices (MUTCD) or the ITE handbook. For reference, detailed explanations for each engineering countermeasure discussed in this summary are available in Making Intersections Safer: A Toolbox of Engineering Countermeasures to Reduce Red Light Running (ITE, 2002), Engineering Countermeasures to Reduce Red Light Running. Bonneson *et al.*, 2002), and Guidance for Using Red Light Cameras.(FHWA/NHTSA, 2003).

In recent work, researchers have examined the relationships between a range of factors and red-light-running frequency (Bonneson *et al.*, 2002). The factors examined include:

- approach flow rate,
- cycle length,
- yellow interval duration,
- heavy-vehicle percentage,
- running speed,
- clearance path length,
- platoon ratio,
- approach grade,
- number of approach lanes,
- light emitting diode (LED) signals,
- use of signal head back plates, use of advance detection, and
- signal head mounting.

In general red light running violations and crashes are:

- negatively associated with approach flow rates,
- negatively associated with yellow indication duration,
- positively associated with approach speeds,
- negatively associated with clearance path length (i.e., a wider intersection),

• positively associated with platoon density, and
• negatively associated with the addition of signal head back plates.

Table 1 summarizes the effectiveness of engineering countermeasures. The information presented reflects findings from before-and-after studies, the calibration of a red-light running regression model, and a review of the literature. The effectiveness of each countermeasure is based on the study of red light running at 10 intersections in Texas. The authors mentioned: "Nevertheless, while a reported crash reduction percentage should be considered "approximate", the fact that it is negative should be taken as strong evidence that the associated countermeasure will reduce the frequency of red light running."

Table 1: Engineering countermeasures to red light running [source: Bonneson et al., 2002]

Countermeasure Category	Specific Countermeasures	Reported Effectiveness[1]	
		RLR	RLR crashes
Signal operations (modify signal phasing, cycle length, or change interval)	Increase the yellow interval duration	– 50 to –70%	–
	Provide green extension	– 45 to –65%	–
	Improve signal coordination	Varies[2]	–
	Improve signal operation (increase cycle length 20 seconds)	– 15 to –25%[3]	–
Motorist information (provide advance information or improved notification)	Improve sight distance	–	–
	Improve visibility of signal (12" lens, add heads)	–	– 33 to –47%
	Improve visibility of signal with yellow LEDs	– 13%	–
	Increase conspicuity of signal (back plate)	– 25%	–32%
	Add advance warning signs without flashers	–	–44%
	Add advance warning signs with active flashers	–29 to –67%	–
Physical improvement (implement safety or operational improvements)	Remove unneeded signals	–	–24%
	Add capacity with additional traffic lanes	–	–
	Flatten sharp vertical curves	–	–

Notes:
1. Negative values indicate a reduction. "–": data not available.
2. RLR frequency is likely to increase with improved coordination; however, this increase may be offset by the larger cycle length typically required for good progression.
3. Reduction associated with an increase in cycle length may not be realized if motorist delay increases significantly.

For applying any of these engineering countermeasures one would need to know the safety status of the intersection prior to installation. In addition, the uncertainty of these estimates is not clear or provided, and so further details would be needed in order to use the estimates in Table 1 for an actual implementation. Moreover, the frequency of red-light-running-related crashes may change as a result of a countermeasure but this alone is not a sufficient measure of success (as is described in detail in this report), and in fact severity of crashes must be considered to appreciate the full impact on safety. Nonetheless, it appears that some improvements in red light running and related crashes are possible with traditional engineering countermeasures.

The effectiveness of RLC programs

The literature review was performed on the basis of a currently published synthesis (McGee and Eccles, 2003) and a critical review of the multi-jurisdiction evaluation of red light cameras (Persaud *et al.*, 2005). These critical evaluations of RLC program results and methodologies were extremely useful in the design of this research effort.

Many previous studies have examined the impact of red light cameras on specific crash types, especially right-angle and rear-end crashes, or on crash severities. In most studies, even though the degree of impacts 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. In addition to affecting certain crash types, RLC programs have also had an impact on crash severities. An extremely useful meta-analysis was performed using RLC program results of Howard County, Maryland, and Charlotte, North Carolina (Flannery and Maccubbin, 2002). Meta-analysis is a statistical technique that involves several statistical and graphical methods of analysis to quantitatively summarize the results of several studies and provide an estimate of the average effect of a measure (McGee and Eccles, 2003). The result of meta-analysis is shown in Figure 2, and the evaluation results used in the analysis are summarized in Table 2. By using the skewness test, the modality test, and the outlier test, they confirmed that there were positive effects from the use of red light camera programs — a reduction of approximately 26% in target crashes.

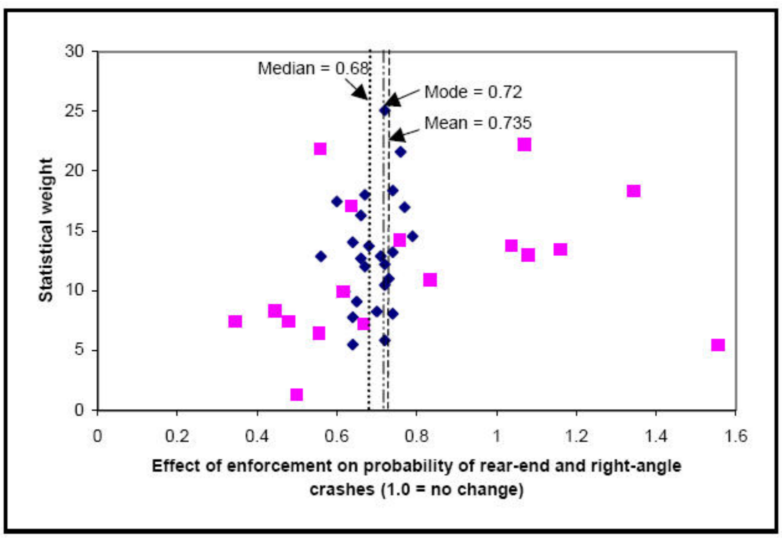

Figure 2: The funnel graph from meta-analysis
[source: McGee and Eccles, 2003]

Table 2: Crash frequency data included in meta-analysis [source: McGee and Eccles, 2003]

Location	Crashes Before*	Crashes After*	Change (%)	Observation Period
Howard County, Maryland				
Little Patuxent Parkway at Columbia Rd.	45	30	−33	2 yr 10 mo B/A
NB Broken Land Parkway at Stevens Forest Rd.	60	43	−28	2 yr 10 mo B/A
NB Broken Land Parkway at Snowden River Pkwy.	50	38	−24	2 yr 9 mo B/A
SB Broken Land Parkway at Snowden River Pkwy.	41	27	−34	2 yr 9 mo B/A
SB Broken Land Parkway at Cradlerock North	34	23	−32	2 yr 9 mo B/A
SB Broken Land Parkway at Stevens Forest Rd.	36	20	−44	2 yr 9 mo B/A
NB Cedar Lane at Hickory Ridge Rd.	22	12	−36	2 yr 8 mo B/A
EB Governor Warfield at Little Patuxent Pkwy.	39	30	−23	2 yr 8 mo B/A
NB Little Patuxent Pkwy. at Governor Warfield	33	26	−21	2 yr 7 mo B/A
SB Little Patuxent Pkwy. at Governor Warfield	31	22	−29	2 yr 5 mo B/A
SB Route 1 at Guilford Rd.	37	33	−40	2 yr 5 mo B/A
NB Route 1 at Guilford Rd.	31	23	−26	2 yr 5 mo B/A
SB Route 29 at Rivers Edge	25	18	−28	2 yr 5 mo B/A
Cedar Lane at Freetown Rd.	20	14	−30	2 yr 5 mo B/A
Route 32 at Route 144	26	16	−38	2 yr B/A
WB Route 40 at Chatham Rd.	23	15	−35	2 yr B/A
WB Route 40 at Rogers Ave.	43	32	−26	2 yr B/A
SB Route 29 at Route 216	26	19	−27	2 yr B/A
SB Broken Land Pkwy. at Hickory Ridge	29	21	−28	2 yr B/A
EB Snowden River at Oakland Mills	36	23	−36	1 yr 11 mo B/A
WB Snowden River Pkwy. at Broken Land Pkwy.	32	21	−34	1 yr 10 mo B/A
EB Route 40 at Rogers Ave.	30	20	−33	1 yr 8 mo B/A
WB Snowden River Pkwy. at Oakland Mills Rd.	19	14	−26	1 yr 6 mo B/A
WB Little Patuxent Pkwy. at Columbia Rd.	14	9	−36	1 yr 6 mo B/A
EB Route 40 at Marriottsville Rd.	14	10	−28	1 yr 4 mo B/A
Charlotte, North Carolina				
Beatties Ford Rd./Hoskins Rd.	4	2	−50.00	3 years B/A
Morehead St./College St.	29	10	−65.52	3 years B/A
Tyvola Rd./Wedgewood Dr.	27	12	−55.56	3 years B/A
Morehead St./McDowell St.	18	10	−44.44	3 years B/A
Brookshire Freeway/Hovis Rd.	44	28	−36.36	3 years B/A
11th St./Brevard St.	26	16	−38.46	3 years B/A
Arrowood Rd./Nations Ford Rd.	9	14	55.56	3 years B/A
N. Tryon St./Harris Blvd.	43	46	6.98	3 years B/A
South Blvd./Archdale Dr.	25	29	16.00	3 years B/A
Westinghouse Blvd./S. Tryon	23	11	−52.17	3 years B/A
Poplar St./4th St.	24	20	−16.67	3 years B/A
Albemarle Rd. at Harris Blvd.	61	34	−44.26	3 years B/A
Sharon Amity Rd. at Central Ave.	32	43	34.38	3 years B/A
Eastway Dr. at Kilborne Dr.	25	27	8.00	3 years B/A
Fairview Rd. at Sharon Rd.	27	28	3.70	3 years B/A
Idlewild Rd. at Independence Blvd.	33	25	−24.24	3 years B/A
Randolph Rd. at Sharon Amity Rd.	18	12	−33.33	3 years B/A

However, even though the result of meta-analysis is not surprising, the regression-to-the-mean and spillover effects could not be accounted for in this meta-analysis. A similar summary of the RLC programs is shown in Table 3 (updated from Persaud *et al.*, 2005), where RLR refers to red light running. Like the previous results of meta-analysis, the review reported that the installation of red light cameras has reduced the number of right-angle crashes and injury crashes, while it has increased rear-end crashes. However, the results of many studies may suffer from regression-to-the-mean or spillover effects, as indicated in the table.

Table 3: Summary of evaluation results [source: Persaud et al., 2005]

Reference	City	Camera Sites	Comparison/Reference Group	Crash Type Studied and Estimated Effects (negative indicates reduction)		Comment
Hillier *et al.* (1993)	Sydney, Australia	Installed at 16 intersections	16 signalized intersections	Right-angle and left-turn opposed	-50%	RTM, spillover and adjusted signal timing in middle of study period are a factor in results
				Rear-end	+25-60%	
South *et al.*(1988)	Melbourne, Australia	Installed at 46 intersections	50 signalized intersections	No significant results. Looked at Right Angle, Right Angle (Turn), Right Against Thru, Rear End, Rear End (turn), Other, All crashes, No. of casualties, No significant results		RTM possible, no accounting for changes in traffic volumes. Comparison sites may have been affected by spillover and other treatments
Andreassen (1995)	Victoria, Australia			No significant results		Lack of an effect may be due to the fact that the sites studied tended to have few red-running related accidents to begin with (author). Comparison sites may have been affected by spillover.
Kent *et al.* (1995)	Melbourne, Australia	3 intersection approaches at different intersections	Non-camera approaches	No significant relationship between the frequency of crashes at RLC and non-RLC sites and differences in red light running behavior		Cross-sectional design is problematic and there were likely spillover effects to the non-camera approaches at the same intersections.
Mann *et al.* (1994)	Adelaide, Australia	Installed at 13 intersections	14 signalized intersections	Reductions at the camera sites were not statistically different from the reductions at the comparison sites.		RTM and spillover a factor
London Accident Analysis Unit (1997)	London, U.K.	RLC at 12 intersections and 21 speed cameras	City-wide effects looked at.	No significant results.		The results are polluted by the fact that two programs are being evaluated
Hooke *et al.* (1996)	Various cities in England and Wales	Installed at 78 intersections		All injury	-18%	A simple before-and-after comparison, not controlling for effects of other factors, regression to the mean and traffic volume changes
Ng *et al.* (1997)	Singapore	Installed at 42 intersections	42 signalized intersections	All	-7%	RTM and spillover effects likely affect results
				Right-angle	-8%	

Reference	City	Camera Sites	Comparison/Reference Group	Crash Type Studied and Estimated Effects (negative indicates reduction)		Comment
Retting and Kyrychenko (2001).	Oxnard, California	Installed at 11 intersections	Unsignalized intersections in Oxnard and signalized intersections in 3 similarly sized cities	All	-7%	Looked at city-wide effects, not just at RLC sites 29 months of before and after data used
				All Injury	-29%	
				Right-angle	-32%	
				Right-angle Injury	-69%	
				Rear-end	+3% (non-significant)	
SafeLight, Charlotte	Charlotte, North Carolina	Installed at 17 intersections	No comparison group	Angle - all approaches	-37%	Probable RTM in site selection
				Angle - camera approaches	-60%	
				All - camera approaches	-19%	
				Rear-end - camera approaches	+4%	
				All	< -1%	
Maryland House of Delegates (2001)	Howard County, Maryland	Installed at 25 intersections		Rear-end	-32%	Probable RTM in site selection
				Right-angle	-42%	
				Other	-22%	
Fleck and Smith (1998)	San Francisco, California	Installed at 6 intersections	City-wide effects looked at	City-wide injury collisions caused by red-light violators. It is not clear how these were defined.	- 9%	Question on definition of RLC crashes. Did not examine specific effects at treated sites.
Vinzant and Tatro (1999)	Mesa, Arizona	6 intersections with RLC only 6 with RLC plus photo speed enforcement	6 signalized intersections	Total crash rates – crashes per million entering vehicles at each intersection		It is not clear whether the assignment of treatment/no treatment to the four quadrants was random.
				Combined-treatment quadrant;	- 15.9%	
				Photo-radar quadrant	- 7.5%	
				RLC quadrant	- 9.7%	
				Control quadrant	- 10.7%	
Fox (1996)	Glasgow, Scotland	Installed at 8 intersections and 3 pelican crossings.	Area-wide effects on injury crashes looked at.	Crossing Carelessly	- 54%	RTM effects likely. Because the decreases in non-RLR crashes are greater than the RLR decreases at times, it is difficult to say what citywide effect the cameras have
				Unsafe Right Turn	- 29%	
				Fail to Keep Distance	+ 8%	
				Other	- 29%	
				All per month	- 32%	
Winn (1995)	Glasgow, Scotland	6 locations on 1 approach	Various	Injury crashes related to RLR violations	- 62%	Probable RTM effects.

The literature reviewed showsthere is a preponderance of evidence indicating that red light running camera systems improve the overall safety of intersections where they are used, even though the results are not yet conclusive. Specifically, angle crashes are typically reduced, while rear-end crashes typically increase. However, there are potential errors due to the disregarding of the regression-to-the-mean and/or spillover effects. Thus, a carefully designed study needs to account for possible regression to the mean and/or spillover effects.

Data summary across Cities

Based on the lessons from the literature review, surveys were distributed to jurisdictions in Arizona, as mentioned previously. Although five jurisdictions were contacted, only four had centralized access to the various sources of data, and only two had either sufficiently large datasets or organized data able to support this research effort. As a result, the cities of Phoenix and Scottsdale serve as the basis for this analysis. The survey requested a great deal of information from each jurisdiction such as the operation of their RLC systems, the crash histories of the RLC intersections, and information on “comparison” intersections. The data were transferred from paper surveys into a relational database. By using these developed database structures, the Survey Findings are summarized, and the survey form is attached in the appendix.

In the following section, the Survey Findings are described with the most relevant results summarized. The questionnaires administered to jurisdictions consisted of questions in four basic categories: General RLC Enforcement Program description, Crash Data, Site Specifics and Signal Phasing, and Publicity and Supplemental Enforcement Campaigns.

General RLC Enforcement program description

Table 4 provides the Survey Findings of the general RLC enforcement programs employed in two jurisdictions within the state of Arizona. Among 25 intersections, red light cameras are installed and operating at 17 intersections, while 9 intersections in Scottsdale are non-operable but still being used as “dummy” cameras.

The 9 dummy cameras serve as useful tools for assessing the potential spillover effects of cameras. Spillover effects are possible and/or likely at many different locations due to the lack of awareness of drivers on camera installation. It is possible that many drivers will not know that the “dummy” cameras are inoperable. It is also possible that many (or a subset of all) drivers do not know which intersections have cameras and which do not. Finally, it is possible that behavior modification induced by RLCs impacts the behavior of drivers at non-RLC locations. Thus, the 9 dummy RLC intersections will be incorporated into the analysis in addition to other intersection locations to assess spillover effects.

Table 5 shows the approach directions of red light cameras at intersections and the dates of their activation or deactivation. At most intersections, the cameras were/are installed on only one intersection approach; however, on 35th Ave & Dunlap Ave (#4), they were deployed on two approaches.

Table 4: Survey findings: general RLC enforcement program description

Questionnaire	Scottsdale	Phoenix
Number of intersections with RLCs	*14 (1 site is overlapped)* *- 6 working new system* *- 9 old system, but still stand as dummy.*	*11*
Total number of signalized intersections	260	940
Typical camera configuration	*Front and rear camera on one approach*	*Front and rear camera on one approach (10 sites)* *Front and rear camera on two approaches (1 site)*
Camera rotation	*New cameras(6) : Not rotated* *Old camera (6): Were rotated*	No
RLR definition	Curb line extended and 0.1 sec delay Grace period : 0.2 sec	Curb line extended and 0.1 sec delay
Constant RLR definition over all intersections	Yes	Yes
RLR citation	Driver	Photographed Driver (who must be vehicle owner)
RLR fine	$185	$203 or $175 + traffic school + traffic survival school
Points added to record	No	Yes
Successful citations	54%~81%	32%
Standard for selecting RLC intersection	- High accident locations - History of RLR accidents - City-wide coverage	- High accident locations - History of RLR accidents - Geographic condition for hardware - City-wide coverage
Evaluation	No	Yes

Table 5: General description of RLC intersections

City Name	Number	Intersection Name	Direction	Date Activated	Date De-activated
Phoenix	1	40th St & Cactus Rd	EB	2001/09/01	
	2	51st Ave & Indian School Rd	WB	2001/09/01	
	3	40th St & Bell Rd	WB	2001/10/01	
	4	35th Ave & McDowell Rd	SB/NB	2001/10/01	
	5	35th Ave & Dunlap Ave	WB	2001/11/01	
	6	12th St & Indian School Rd	EB	2001/11/01	
	7	7th Ave & Greenway Rd	WB	2001/12/01	
	8	32nd St & McDowell Rd	WB	2001/12/01	
	9	48th St & Ray Rd	EB	2001/12/01	
	10	19th Ave & Thunderbird Rd	WB	2001/12/01	
	11	7th St & Bell Rd	WB	2003/12/01	
Scottsdale	12	68th Street & Camelback	WB	1996/12/01	2001/11/30
	13	Scottsdale & McDowell	NB	1996/12/01	2002/10/31
	14	Scottsdale & Doubletree	NB	1996/12/01	2001/12/31
	15	Scottsdale & Shea	SB	1996/12/01	2003/04/30
	16	Hayden & McDonald	SB	1996/12/01	2003/04/30
	17	Hayden & McDowell	NB	1996/12/01	2003/04/30
	18	Hayden & Shea	EB	1996/12/01	2001/12/31
	19	Scottsdale & Mercer	SB	1997/02/01	2003/01/31
	20	Scottsdale & Thomas	SB	2001/02/01	2002/10/31
	21	Scottsdale & Thomas	NB	2002/10/01	
	22	Scottsdale & Cactus	NB	2002/10/10	
	23	Hayden & Indian School	SB	2002/10/26	
	24	Pima & Pinnacle Peak	SB	2003/01/31	
	25	Hayden & McCormick	NB	2003/04/07	
	26	Scottsdale & Frank Lloyd Wright	NB	2003/04/28	

Crash Data

Accurate and comprehensive crash data are, of course, imperative for a successful analysis. Each jurisdiction participating in the survey provided crash data for their RLC intersections. The brief summary of the crash data is provided in Table 5. It should be noted that the accident reporting threshold changed in two jurisdictions, suggesting that crash counts before and after these changes are not directly comparable. Attempts are made to account for this in the analysis.

Table 7 shows summary statistics for crashes that occurred in the study jurisdictions. In the table, "Crashes at RLC intersections" means the average number of crashes per year at an RLC intersection. The crash frequencies are large because they include Property Damage Only (PDO) accidents as well as fatal and injury accidents.

In Scottsdale, the mean value of crashes at the RLC intersections (33.77/year /intersection) is higher than that of non-RLC intersections (0.82/year/intersection), while, in Phoenix, the difference in the mean value of crashes between RLC intersections and non-RLC intersections are relatively smaller than in Scottsdale. This is because the 14 comparison sites in Phoenix were sampled from intersections with the highest number of intersection-related collisions.

Table 6: Survey findings: crash data

Questionnaire	Scottsdale	Phoenix
Crash data of RLC intersection	Yes	Yes
Years of crash data	1990-2004	1998-2003
Crash data of non-RLC intersections	Yes	Yes (Of 14 intersections with the highest number of accidents)
Reporting by	Police only	Police only
Reporting threshold	$1,000 (increased from $500 in 1991)	$1,000
De-personalized copies of all crash reports	No	No

In Table 7, the citywide crashes in Phoenix could not be summarized due to lack of data. More detailed information on crashes is discussed in the next section.

Table 7: Summary statistics of the number of crashes per year per intersection in study jurisdictions

City Name	Variable	Mean	Median	Min	Max	Years of Data
Phoenix	City-wide Crashes	-	-	-	-	1998/10~2003/09
	Crashes in non-RLC intersections	24.50	23.60	13.8	41.6	
	Crashes in RLC intersections	36.18	35.4	9.4	55.8	
Scottsdale	City-wide Crashes	0.93	0.07	0.07	65.93	1990~2003
	Crashes in non-RLC intersections	0.82	0.07	0.07	65.93	
	Crashes in RLC intersections	33.77	34.25	14.50	52.71	

Site specifics and Signal phasing

Table 8 shows the Survey Findings regarding RLC site specifics and signal phasing. Obtained from the survey were various variables such as traffic volume and signal data.

No jurisdictions simultaneously installed RLCs; as expected RLCs were phased in over time. Scottsdale changed the signal timing plan at one intersection in after installing red light cameras (#20: Scottsdale & Thomas). Among 24 intersections, 22 intersections are part of a signal progression, whereas 2 intersections in Scottsdale (#12: 68th street & Camelback and #24: Pima & Pinnacle Peak) are not part of a signal progression. All RLC intersections are using all-red intervals that are calculated using the ITE standard.

Table 8: Survey findings: site specifics and signal phasing

Questionnaire	Scottsdale	Phoenix
Site drawing	Yes (Aerial photo)	Yes (CAD file)
Other improvements when RLCs installed	No	No
Record of any changes at signalized intersection	Yes	N/A
Traffic count on the RLC intersections	Yes (ADT)	Partially, Yes (ADT)
Traffic count on other signalized intersections	Yes (ADT)	Yes (ADT)
Traffic count on un-signalized intersections	Yes (ADT)	No
Progression	Yes, except 2 intersections	Yes
Yellow interval of RLC intersection	Yes	Yes (But, hard to find it due to unknown speed limits)
Standard of Yellow interval	ITE standard equation	ITE standard equation
Use all-red interval on the RLC intersection	Yes	Yes
Use all-red interval on the non-treated intersection	Yes	Yes
Yellow interval Change after installing RLCs	Scottsdale & Thomas: NST: 3.6→ 4.0 sec. EWT: 3.6→ 4.0 sec.	-

Site Publicity and Supplemental Enforcement Campaigns

The final section of the survey requested information regarding RLC site publicity and supplemental enforcement campaigns. Table 9 shows the results of the final section of the survey.

Phoenix installed warning signs on all approaches to RLC intersections. Scottsdale, deployed warning (informational) signs at only two intersections (#15: Scottsdale & Shea and #18: Hayden & Shea) and only on target approaches.

Table 9: Survey findings: site publicity and supplemental enforcement campaigns

Questionnaire	Scottsdale	Phoenix
Warning sign	Yes (target approaches at 2 intersections)	Yes (All approaches at RLC intersections)
Level of public program	High: Old system Limited : New system	Medium
Sign to show the number of ticketed violations	No	No
Supplemental enforcement at non-RLC sites	No	No

Data Summary within Cities

In this section, crash, traffic volume, and signal phasing data are summarized. In addition, it is necessary to consider and develop working definitions of RLC related crashes, that is, crashes determined to be affected by the presence of RLCs. While a careful analysis (to follow) will consider several different alternative definitions, at this point three criteria are discussed. Employing a definition of RLC related crashes will enable an initial examination of the potential effect of RLCs at intersections.

City of Scottsdale

A. Crash Data

City-wide Crashes

The trend of crashes in Scottsdale was summarized and the duration of data and the number of crashes used in the analysis are as follows:

- Duration of data: January 1990 to December 2003
- Number of crashes : 57,155 over 14 years

Table 10 and Figure 3 show the number and the percentage of crash types that occurred from January 1990 to December 2003. The number of rear-end crashes was 22,324 out of a total 57,155 crashes (39%), while the second most frequent crash type was angle crashes (9,386 or 16%).

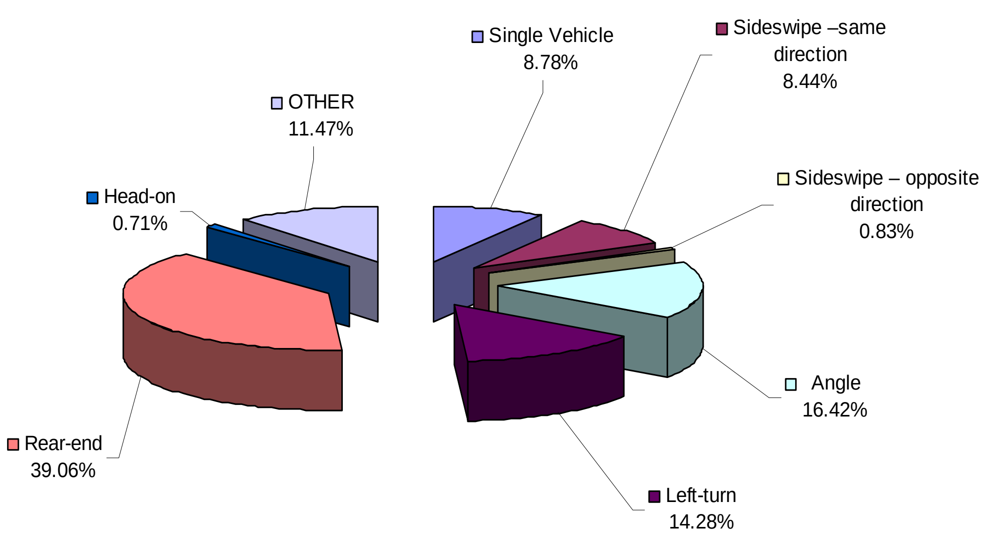

Figure 3: Percentage of crash type in Scottsdale for 14 year period

The crash trends in Scottsdale suggest that an effort to reduce angle crashes through the use of RLCs may be worthwhile, since angle crashes are generally more severe than rear-end crashes.

Table 10: The number of crashes in Scottsdale by year and crash type

Year	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear -end	Head-on	OTHER	Total
1990	431	190	23	521	452	1011	12	235	2875
1991	339	203	19	513	414	851	26	228	2593
1992	405	262	30	560	423	1193	13	271	3157
1993	439	340	18	688	570	1418	15	392	3880
1994	269	334	37	664	610	1526	48	583	4071
1995	303	407	44	719	633	1635	34	661	4436
1996	325	392	41	754	726	1943	46	453	4680
1997	310	444	36	848	534	1875	37	420	4504
1998	321	302	20	670	675	1916	32	631	4567
1999	343	393	35	651	798	2095	17	652	4984
2000	385	406	17	804	643	1725	28	508	4516
2001	358	383	33	729	549	1782	25	496	4355
2002	435	399	54	678	612	1788	38	509	4513
2003	357	369	69	587	524	1566	34	518	4024
Total	5020	4824	476	9386	8163	22324	405	6557	57155
Percent	8.78%	8.44%	0.83%	16.42%	14.28%	39.06%	0.71%	11.47%	100%

Figure 4 shows that 63% of total crashes were Property Damage Only (PDO) crashes. Property damage crashes are generally significantly under reported (compared to injury and fatal crashes) and so these numbers reflect an unrealistic lower limit. These data represent crashes at both signalized and unsignalized intersections.

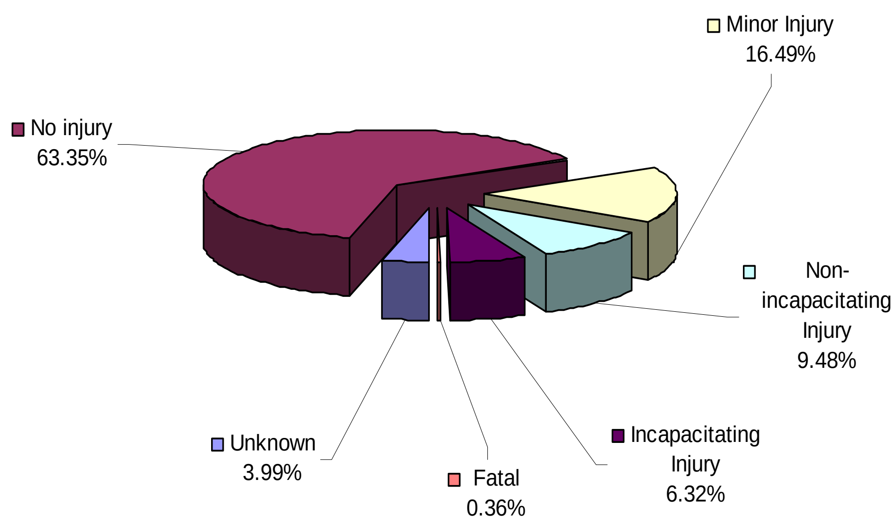

Figure 4: Percentage of each crash severity in Scottsdale

Crashes at RLC Intersections

The trend of crashes in Scottsdale was summarized and the duration of data and the number of crashes used in the analysis are as follows:

- Duration of data: January 1990 to December 2003
- Number of crashes: 6,618 over 14 years

Table 11 shows the average number of crashes per year by crash type, while Table 12 provides descriptive statistics. On average 33.7 crashes per year occurred at RLC intersections. Rear-end crashes (18.16/year average) were more frequent than angle crashes (3.72/year average).

Table 11: Number of crashes per year by crash type

INT_NAME	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear - end	Head-on	OTHER
68 & CAMELBACK	0.86	1.57	0.29	3.36	8.86	9.14	0.14	2.00
HAYDEN & INDIAN SCHOOL	2.64	4.00	0.14	7.79	7.43	26.21	0.29	3.71
HAYDEN & MCCORMICK	1.14	1.50	0.07	1.79	2.86	10.71	0.00	1.21
HAYDEN & MCDONALD	1.07	1.21	0.21	2.71	0.86	16.21	0.07	1.36
HAYDEN & MCDOWELL	1.29	3.64	0.50	5.86	4.07	16.93	0.00	2.14
HAYDEN & SHEA	1.71	3.86	0.14	3.29	4.57	35.79	0.14	1.86
PIMA & PINNACLE PEAK	0.71	1.07	0.29	2.57	5.21	3.07	0.00	1.57
SCOTTSDALE & CACTUS	0.57	3.50	0.14	2.43	8.93	18.79	0.29	1.79
SCOTTSDALE & DOUBLETREE	1.79	1.00	0.14	1.43	4.36	13.50	0.14	0.93
SCOTTSDALE & FRANK LW	1.00	4.07	0.21	2.21	4.43	19.29	0.14	2.71
SCOTTSDALE & MCDOWELL	1.64	6.21	0.21	5.29	3.93	27.57	0.14	3.86
SCOTTSDALE & MERCER	0.29	1.00	0.00	4.21	3.36	4.14	0.00	1.64
SCOTTSDALE & SHEA	0.64	4.86	0.07	3.86	4.93	23.64	0.14	2.86
SCOTTSDALE & THOMAS	1.07	7.14	0.00	5.36	5.14	29.29	0.29	4.43

Table 12: Summary statistics of crashes at RLC intersections by crash types

Statistics	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear - end	Head-on	OTHER
Mean	1.17	3.19	0.17	3.72	4.92	18.16	0.13	2.29
Median	1.07	3.57	0.14	3.32	4.50	17.86	0.14	1.93
Min	0.29	1.00	0.00	1.43	0.86	3.07	0.00	0.93
Max	2.64	7.14	0.50	7.79	8.93	35.79	0.29	4.43

Statistics related to crash severity are shown in Tables 13 and 14. Table 13 shows crash severity by intersection, whereas Table 14 shows summary statistics for crash severity.

Table 13: Number of crashes (per year) by severity

INT_NAME	Unknown	No injury	Minor Injury	Non-Incapacitating Injury	Incapacitating Injury	Fatal	Total
68 & CAMELBACK	0.21	16.21	5.00	3.00	1.64	0.14	26.21
HAYDEN & INDIAN SCHOOL	0.36	36.43	9.07	3.86	2.36	0.14	52.21
HAYDEN & MCCORMICK	0.00	12.57	3.21	2.07	1.36	0.07	19.29
HAYDEN & MCDONALD	0.21	15.29	4.14	2.43	1.57	0.07	23.71
HAYDEN & MCDOWELL	0.86	22.57	6.43	3.00	1.57	0.00	34.43
HAYDEN & SHEA	0.64	34.07	9.64	4.14	2.71	0.14	51.36
PIMA & PINNACLE PEAK	0.21	9.21	2.36	1.71	1.00	0.00	14.50
SCOTTSDALE & CACTUS	0.14	24.21	7.64	2.50	1.79	0.14	36.43
SCOTTSDALE & DOUBLETREE	0.36	15.00	4.36	1.86	1.71	0.00	23.29
SCOTTSDALE & FRANK LW	0.29	24.21	5.86	1.93	1.64	0.14	34.07
SCOTTSDALE & MCDOWELL	0.21	35.07	6.64	3.86	2.93	0.14	48.86
SCOTTSDALE & MERCER	0.29	9.93	2.71	1.00	0.71	0.00	14.64
SCOTTSDALE & SHEA	0.36	29.64	6.43	2.64	1.93	0.00	41.00
SCOTTSDALE & THOMAS	0.36	37.71	8.29	4.86	1.50	0.00	52.71

Table 14: Summary statistics of crashes (per year) at RLC intersections by crash severity

Statistics	Unknown	No injury	Minor Injury	Non-Incapacitating Injury	Incapacitating Injury	Fatal	Total
Mean	0.32	23.01	5.84	2.78	1.74	0.07	33.77
Median	0.29	24.21	6.43	2.50	1.64	0.07	34.43
Min	0.00	9.21	2.36	1.00	0.71	0.00	14.50
Max	0.86	37.71	9.64	4.86	2.93	0.14	52.71

One might be interested to know which crash types are most severe. Table 15 shows the number of crashes per year by crash type and severity. There were a larger number of serious (fatal + incapacitating) rear-end (0.58/year) crashes than angle crashes (0.27/year). However, the proportion of injury and fatal crashes for angle crashes (34.3%) is higher than that for rear-end crashes (30.5%)(see Table 16),. Moreover, the percentage of major injury and fatal crashes for angle crashes (58.6%) is significantly higher than that of rear-end crashes (29.6%). Thus, in Scottsdale (at signalized intersections) it appears that angle crashes result in more serious crashes, on average, than rear-end crashes.

Table 15: Number of crashes (per year) by crash type and severity

Type / Severity	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear - end	Head-on	OTHER
Unknown	0.13	0.05	0.00	0.03	0.01	0.08	0.01	0.03
No Injury	0.71	2.86	0.13	2.43	2.77	12.58	0.06	1.47
Minor Injury	0.12	0.14	0.03	0.53	0.87	3.88	0.04	0.24
Non-incapacitating Injury	0.11	0.08	0.01	0.47	0.68	1.06	0.01	0.35
Incapacitating Injury	0.09	0.06	0.01	0.26	0.56	0.57	0.02	0.18
Fatal	0.01	0.00	0.00	0.01	0.03	0.01	0.01	0.02
Total	1.17	3.19	0.17	3.72	4.92	18.16	0.13	2.29

Table 16: Proportion of crashes by crash type and severity

Type / Severity	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear - end	Head-on	OTHER
PDO	68.3%	91.1%	76.5%	65.7%	56.3%	69.5%	45.8%	65.2%
Injury and Fatal	31.7%	8.9%	23.5%	34.3%	43.7%	30.5%	54.2%	34.8%
Minor	36.9%	50.9%	62.5%	41.4%	40.6%	70.4%	53.8%	30.5%
Major Injury and Fatal	63.1%	49.1%	37.5%	58.6%	59.4%	29.6%	46.2%	69.5%

Figures 5 and 6 provide additional information regarding crash severity. In these figures, PDO refers to crash type "No Injury", while and "Major" refers to crashes with injuries or fatalities.

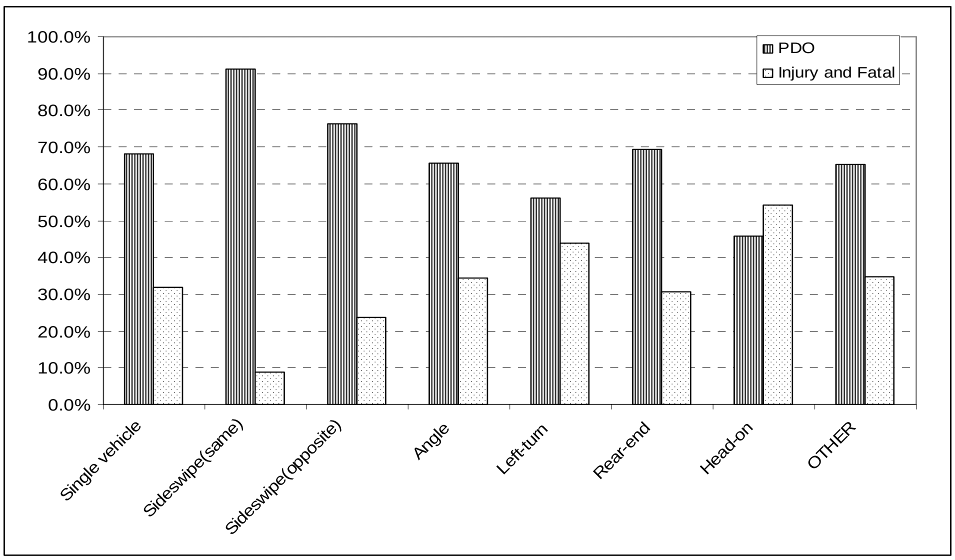

Figure 5: Percentage of crashes per year by crash type and severity (PDO vs. injury and fatal)

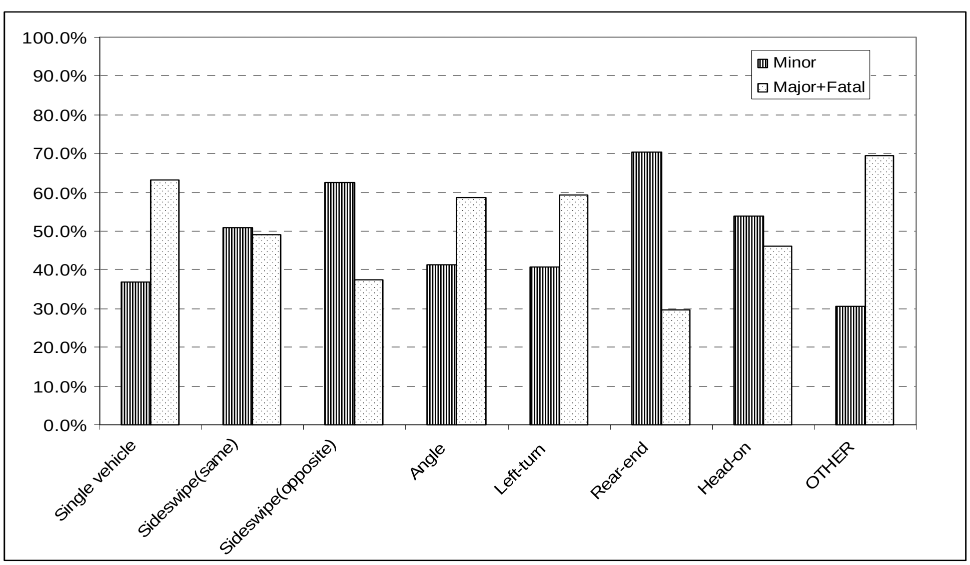

Figure 6: Percentage of crashes (per year) by crash type and severity (minor vs. major and fatal)

What Crashes Are Influenced by Red Light Cameras?

As mentioned previously, the objective of this research is to evaluate the impact of red light cameras (RLCs) on safety. In order to evaluate the impact of RLCs on crash occurrence, it is necessary to understand which crash types are affected by RLCs—referred to as target crashes. To better understand this, consider the following. Assume that run-off-road crashes increased after installation of RLCs. If, however, run off road crashes are materially unaffected by RLCs, then the observed increase in these crash types is attributable to other factors. Thus, a proper analysis must identify only those crashes that will be materially affected by the installation of RLCs. It is generally accepted that RLCs have the potential to reduce angle crashes at signalized intersections and possibly increase rear-end crashes on the intersection approaches (McGee and Eccles, 2005).

In theory, the presence of RLCs reduces the occurrence of red light running and thereby reduces the possibility of related angle and left-turning 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 a following vehicle to hit the lead vehicle. These potential crash types are made worse when lead vehicles are large, limiting visibility of following vehicles. Therefore, crashes related to RLCs can be divided into two-crash types: crashes attributed to red light running (hereafter RLR crashes) and the crashes caused by the behavior to avoid red light running (hereafter ARLR crashes).

To distinguish between the RLR crashes and the ARLR crashes, they are divided using the record of violations of drivers involved in a crash. If one of the drivers involved in a crash violated the traffic signal red indication, then it is determined to be a RLR crash. When a signal indication was not violated, a crash is determined to be an ARLR crash.

RLC related crashes cannot be identified using only these two criteria. Other factors, such as crashes occurring far from the intersection, or crashes involving intoxicated drivers, may not be associated with RLCs in any way. To identify RLC related crashes, three filter criteria were used:

1. Distance from crash occurrence location to the center of intersection,
2. Drivers' physical condition (impaired drivers excluded)
3. Vehicles' prior action

Each of these three criteria is discussed in the following paragraphs. Figure 7 depicts the process used to filter all potential crashes and derive a set of target crashes.

Criteria 1: Where did the crash occur?

Suppose that a crash occurred at a certain point fairly distant from the center of an RLC intersection. This fact reduces the likelihood that a RLC affected this crash. For example, if a crash occurred 1500 feet from the center of an intersection, it is likely that the RLC had only a minor, if any, affect on the crash. It is possible of course that a sudden stop would affect a number of following vehicles and cause a rear-end crash far from the center of intersection. However, given knowledge of driver reaction times and the fact that most drivers are predominantly focused on the vehicle immediately in front of their vehicle, it is assumed that a RLC related crash of this type is a low probability event. As a result, crashes that occurred farther than 100 feet from the intersection were determined to not be RLC related crashes.

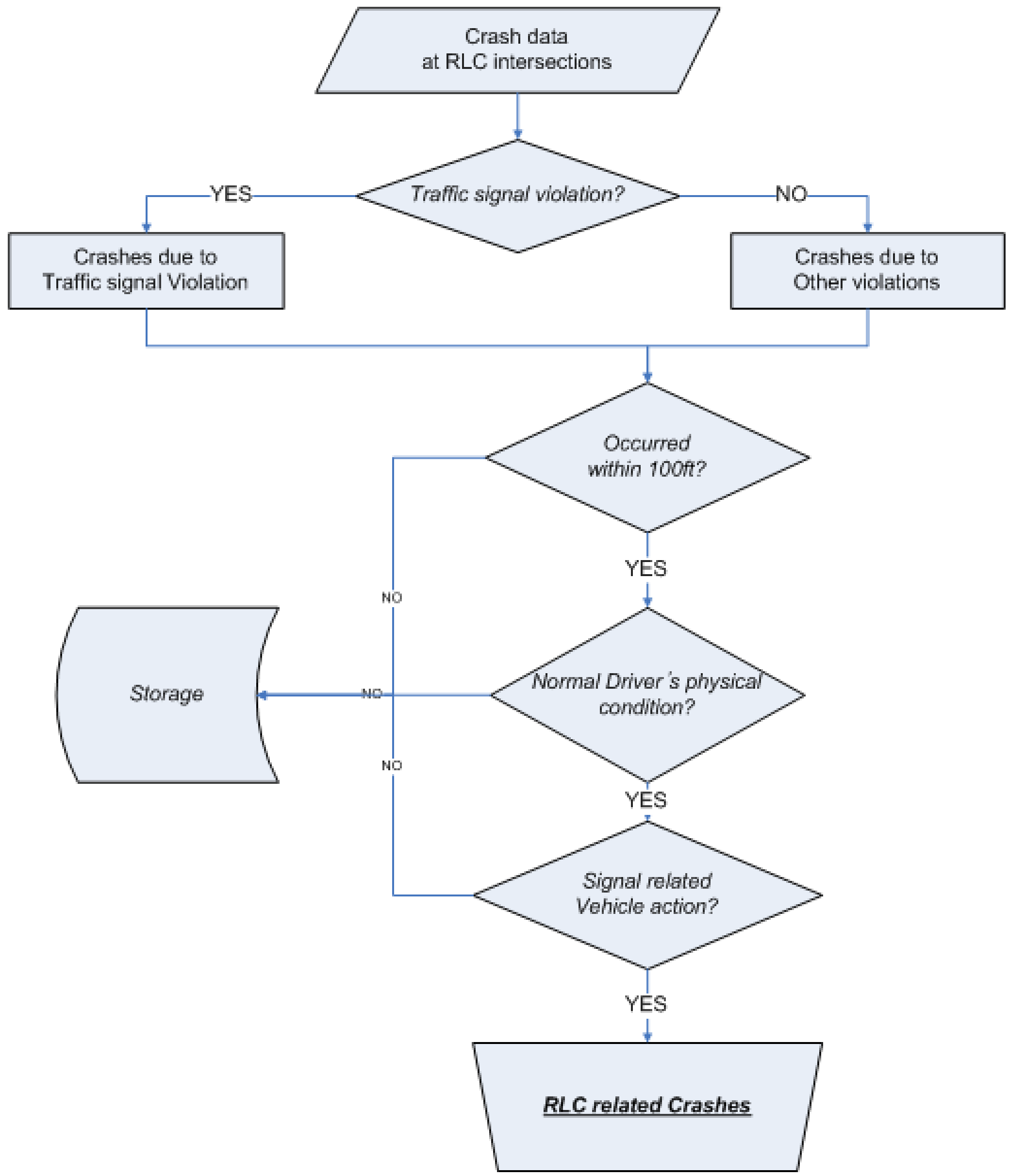

Figure 7: Selection process for RLC crashes

Criteria 2: What was the driver's physical condition?

Crashes that involved factors such as heavy drinking, the influence of drugs, ill-ability influenced, and sleepiness/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. As a result only crashes where drivers had "No apparent defects" were considered as being potentially RLC related.

Criteria 3: What were the vehicle's actions?

Last but not least, a vehicle's action is considered. Table 17 lists 26 vehicle actions that describe possible actions prior to vehicle crashes. Of these vehicle actions, 19 marked with "×" are assumed not to be affected by the presence of a RLC. Thus, any crash that involved a vehicle action with "×" is not a target crash and is assumed to NOT be affected by RLCs at the intersection.

Table 17: Vehicle action and RLR

Vehicle Action	Affected by Red Light Camera?	Vehicle Action	Affected by Red Light Camera?
Avoiding Vehicle or Objects	○ (yes)	Making Right Turn	×
Backing	× (no)	Making U-Turn	○
Changing Lanes	○	Other Action	×
Crossing Road	×	Overtaking or Passing	×
Driverless Moving Vehicle	×	Properly Parked	×
Entering Alley or Driveway	×	Slowing in Traffic	○
Entering Parking Position	×	Standing	×
Getting On or Off Vehicle	×	Stopped in Traffic	○
Improperly Parked	×	Straight	○
Leaving Alley or Driveway	×	Unknown Action	×
Leaving Parking Position	×	Walking Against Traffic	×
Lying	×	Walking with Traffic	×
Making Left Turn	○	Working on or pushing vehicle	×

RLC Crashes at RLC intersections

Using the previously mentioned criteria, 2496 out of 6618 crashes occurring at RLC intersections are determined to represent RLC crashes. Among these, 481 crashes are RLR crashes and 2015 crashes are ARLR crashes. To summarize:

- Duration of data: January, 1990 to December, 2003
- Number of intersections: 14
- Number of RLC crashes: 2496/14 years
- Number of RLR crashes: 481/14 years
- Number of ARLR crashes: 2015/14 years

Table 18 shows the mean values of the RLC crashes by crash type. About 12.73 crashes occur per year at RLC intersections. As expected, the number of ARLR crashes (10.28/year) is higher than that of RLR crashes (2.45/year). In addition, the proportion of angle crashes in the RLR crashes (52%) is relatively large while the proportion of rear-end crashes associated with RLR crashes (0.81%) is small. In contrast, the proportion of rear-end crashes associated with ARLR crashes (62%) is relatively large.

Table 18: Mean value of the RLC crashes by crash type

Crash Type / Mean	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear - end	Head-on	OTHER	Total
RLR crashes	0	0.00	0.02	1.28	1.08	0.02	0.01	0.05	2.45
ARLR crashes	0	0.76	0.03	0.43	2.50	6.34	0.04	0.18	10.28
RLC crashes	0	0.76	0.05	1.71	3.58	6.36	0.05	0.23	12.73

With respect to crash severity, Table 19 and Figure 8 show that RLR crashes are more dangerous than the ARLR crashes, on average. The percentage of injury and fatal crashes in the ARLR crashes is 31.4%, while in RLR crashes this ratio is about 48.8%.

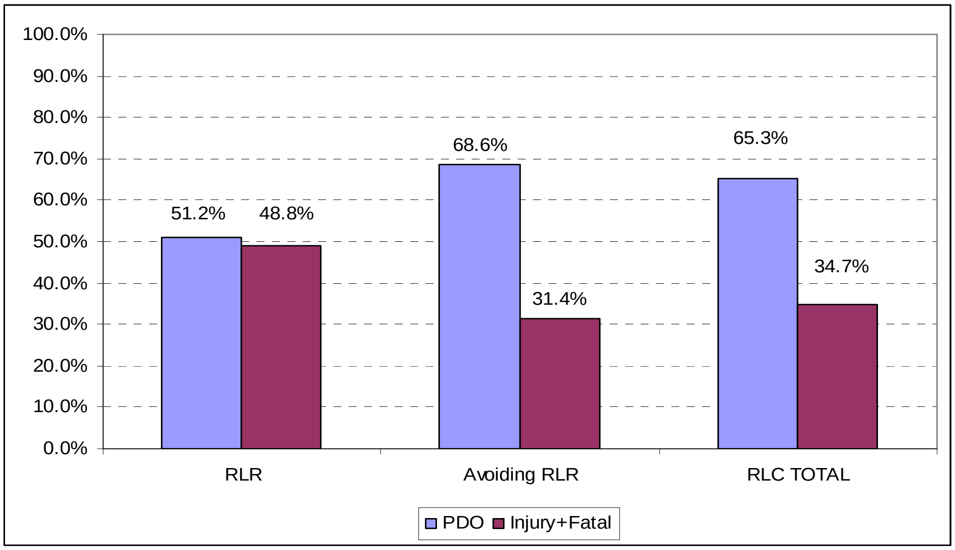

Figure 8: Percentage of PDO vs. injury and fatal crashes

Table 19: Mean value of RLC crashes by severity

Severity / Mean	Unknown	No injury	Minor Injury	Non-Incapacitating Injury	Incapacitating Injury	Fatal	Total
RLR crashes	0.02	1.24	0.44	0.41	0.33	0.01	2.45
Avoiding RLR crashes	0.05	7.03	1.89	0.76	0.54	0.02	10.28
RLC crashes	0.07	8.27	2.33	1.17	0.87	0.03	12.73

Table 20 shows the number of crashes per year by crash type and crash severity. Unlike Table 15, there is slight difference between rear-end crashes (0.2/year) and angle crashes (0.17/year) for serious crashes (fatal + incapacitating injury), even though the difference in the number of crashes between angle and rear-end is large.

Table 20: Number of crashes (per year) at RLC intersections

Severity \ Type	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear - end	Head-on	OTHER
Unknown	0	0.02	0.00	0.02	0.01	0.03	0.00	0.00
No Injury	0	0.69	0.03	0.96	1.93	4.54	0.02	0.10
Minor Injury	0	0.03	0.01	0.28	0.63	1.31	0.02	0.05
Non-incapacitating Injury	0	0.02	0.00	0.29	0.51	0.29	0.01	0.06
Incapacitating Injury	0	0.01	0.01	0.16	0.47	0.20	0.01	0.03
Fatal	0	0.00	0.00	0.01	0.03	0.00	0.00	0.00
Total	0	0.76	0.05	1.71	3.58	6.36	0.05	0.23

In addition, as shown in Table 21, angle crashes appear to be more serious than rear-end crashes. Moreover, the percentage of “Injury and Fatal” and “Major and Fatal” in angle crashes is slightly higher than that of Table 16. For example, the percentage of major and fatal angle crashes in Table 16 is 58.6%, but is 61.5% for the RLR angle crashes. It remains to be determined whether these small differences are significant.

Table 21: Proportion of crashes by crash type and severity

Severity \ Type	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear – end	Head-on	OTHER
PDO	-	92.5%	66.7%	56.9%	54.1%	71.6%	40.0%	44.4%
Injury and Fatal	-	7.5%	33.3%	43.1%	45.9%	28.4%	60.0%	55.6%
Minor	-	54.5%	66.7%	38.5%	38.6%	72.8%	66.7%	36.0%
Major and Fatal	-	45.5%	33.3%	61.5%	61.4%	27.2%	33.3%	64.0%

B. Traffic volume and Signal phasing data

The data extracted from the survey for site specifics and signal phasing are summarized and shown in Table 22.

Table 22: Survey findings: traffic volume and signal phasing data

Intersection Name	Direction	ADT	Count Date	No. of lanes	Yellow Interval (sec)
68th Street & Camelback	NB	-	-	2	4
	SB	-	-	2	4
	EB	-	-	3	4.3
	WB	-	-	3	4.3
Scottsdale & McDowell	NB	20291	1999-05-04	3	4
	SB	25427	1999-05-04	3	4
	EB	20128	1999-05-04	3	4
	WB	19660	1999-05-04	3	4
Scottsdale & Doubletree	NB	29293	2000-04-24	3	4.3
	SB	25158	2000-04-24	2	4.3
	EB	4691	2000-04-24	2	4
	WB	13157	2000-04-24	2	4
Scottsdale & Shea	NB	28729	2000-05-22	3	4
	SB	24369	2000-05-22	3	4
	EB	23012	2000-05-22	3	4
	WB	22069	2000-05-22	3	4
Hayden & McDonald	NB	33391	1998-04-06	3	4.3
	SB	35468	1998-04-06	3	4.3
	EB	8215	1998-04-06	2	4
	WB	8178	1998-04-06	2	4
Hayden & McDowell	NB	12960	1999-05-17	3	4.3
	SB	16709	1999-05-17	3	4.3
	EB	18961	1999-05-17	3	4
	WB	12514	1999-05-17	3	4
Hayden & Shea	NB	11644	2002-05-14	2	-
	SB	9996	2002-05-14	3	-
	EB	28526	2002-05-14	3	-
	WB	24312	2002-05-14	3	-
Scottsdale & Mercer	NB	-	-	3	4
	SB	-	-	3	4
	EB	-	-	2	4
	WB	-	-	1	4
Scottsdale & Thomas	NB	20927	2002-12-03	3	4
	SB	20821	2002-12-03	3	4
	EB	21935	2002-12-03	3	4
	WB	17084	2002-12-03	2	4

Intersection Name	Direction	ADT	Count Date	No. of lanes	Yellow Interval (sec)
Scottsdale & Cactus	NB	20555	2002-01-08	3	4.5
	SB	25045	2002-01-08	2	4.5
	EB	16736	2002-01-08	2	4.5
	WB	17165	2002-01-08	2	4.5
Hayden & Indian School	NB	20786	1999-02-22	3	4.3
	SB	24423	1999-02-22	3	4.3
	EB	17813	1999-02-22	2	4
	WB	12977	1999-02-22	2	4
Pima & Pinnacle Peak	NB	18414	2001-09-12	2	5
	SB	17630	2001-09-12	2	5
	EB	9404	2001-09-12	1	5
	WB	5282	2001-09-12	2	5
Hayden & McCormick	NB	15259	2000-06-13	3	4
	SB	15019	2000-06-13	3	4
	EB	3664	2000-06-13	2	4
	WB	4394	2000-06-13	2	4
Scottsdale & Frank Lloyd Wright	NB	20457	2001-04-16	2	4.8
	SB	21002	2001-04-16	2	4.8
	EB	21206	2001-04-16	2	4.8
	WB	29424	2001-04-16	2	4.8

City of Phoenix

A. Crash data

The duration of data, the number of crashes, and the number of intersections used in the analysis are:

- Duration of data: October 1, 1998 to September 30, 2003 (5 years)
- Number of crashes : 1990
- Number of intersections: 11

Total Crashes at RLC Intersections

Table 23 shows the average number of crashes per year at each RLC intersection. The summary statistics for the number of crashes by crash type are shown in Table 24. The total number of crashes that occurred at RLC intersections in Phoenix (36.18/year) is higher than that of Scottsdale (33.7/year). The number of angle crashes in Phoenix (4.87/year) is higher than that of Scottsdale (3.72/year), while the number of rear-end crashes in Phoenix (13.87/year) is lower than that of Scottsdale (18.16/year).

Table 23: Number of crashes (per year) by crash type

INT_NAME	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear-end	Head-on	Other
12th St & Indian School Rd	1.60	2.00	0.00	3.80	10.20	7.40	0.00	0.20
19th Ave & Thunderbird Rd	0.80	1.60	0.00	4.60	7.60	19.60	0.00	0.60
32nd St & McDowell Rd	2.20	3.40	0.00	8.00	21.40	19.80	0.20	0.80
35th Ave & Dunlap Ave	2.40	2.20	0.00	5.40	23.60	14.40	0.00	1.00
35th Ave & McDowell Rd	2.00	0.20	0.20	7.20	19.40	16.00	0.40	2.00
40th St & Bell Rd	0.40	1.80	0.20	3.00	12.40	16.00	0.20	1.40
40th St & Cactus Rd	0.40	0.40	0.20	4.40	9.00	10.20	0.00	1.20
48th St & Ray Rd	0.20	0.20	0.00	3.00	11.60	11.60	0.20	0.60
51st Ave & Indian School Rd	2.40	2.80	0.00	6.20	19.80	17.00	0.00	1.40
7th Ave & Greenway Rd	0.40	0.60	0.00	2.20	3.20	2.60	0.00	0.40
7th St & Bell Rd	1.20	1.40	0.00	5.80	10.80	18.00	0.00	1.00

Table 24: Summary statistics of crashes in the RLC intersections by crash type

Statistics	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear-end	Head-on	Other
Mean	1.27	1.51	0.05	4.87	13.55	13.87	0.09	0.96
Median	1.20	1.60	0.00	4.60	11.60	16.00	0.00	1.00
Min	0.20	0.20	0.00	2.20	3.20	2.60	0.00	0.20
Max	2.40	3.40	0.20	8.00	23.60	19.80	0.40	2.00

Table 25 shows the number of crashes by severity, while Table 26 provides summary statistics. Injury and fatal crashes of approximately 16.95 per year occurred at RLC intersections of Phoenix, compared to 10.43 per year in Scottsdale.

The intent of comparing statistics across cities is merely to show differences, not to make judgments about programs, intersection designs, drivers, or any other differences between the cities. In other words, it is impossible to determine what factors are "causing" these differences between cities. Moreover, it is even possible that a larger statistic is associated with a safer intersection after differences in exposure and other factors are accounted for.

Table 25: Number of crashes (per year) by severity

INT_NAME	Unknown	No injury	Minor Injury	Non-Incapacitating Injury	Incapacit-ating Injury	Fatal	Total
12th St & Indian School Rd	0	13.6	6.6	3.6	1.2	0.2	25.2
19th Ave & Thunderbird Rd	0	20	9.2	4.2	1.2	0.2	34.8
32nd St & McDowell Rd	0.2	32.2	13.8	6.6	2.8	0.2	55.8
35th Ave & Dunlap Ave	0	23.8	14.2	9.2	1.6	0.2	49
35th Ave & McDowell Rd	0	23	14.6	6.2	3.4	0.2	47.4
40th St & Bell Rd	0	18.6	9	6.2	1.6	0	35.4
40th St & Cactus Rd	0	13.2	7	3.6	1.6	0.4	25.8
48th St & Ray Rd	0	14	7.2	4.8	1.4	0	27.4
51st Ave & Indian School Rd	0.4	27.8	12	7	2	0.4	49.6
7th Ave & Greenway Rd	0.2	4	3.2	1.4	0.6	0	9.4
7th St & Bell Rd	0	20.6	10.2	5.2	2.2	0	38.2

Table 26: Summary statistics of crashes at RLC intersections by severity

Statistics	Unknown	No Injury	Minor Injury	Non-Incapacitating Injury	Incapacitating Injury	Fatal	Total
Mean	0.07	19.16	9.73	5.27	1.78	0.16	36.18
Median	0.00	20.00	9.20	5.20	1.60	0.20	35.40
Min	0.00	4.00	3.20	1.40	0.60	0.00	9.40
Max	0.40	32.20	14.60	9.20	3.40	0.40	55.80

From inspection of Table 27, it can be seen that the number of rear-end crashes resulting in injuries or fatalities (5.67/year) is higher than that of angle crashes (2.41/year), as was found previously. Examination of Table 28, however, again shows that angle crashes are more serious than rear-end crashes.

Table 27: Number of crashes per year by crash type and severity (5-category)

Severity \ Type	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear -end	Head-on	Other
Unknown	0.05	0.00	0.00	0.00	0.02	0.00	0.00	0.00
No Injury	0.35	1.27	0.02	2.29	6.31	8.20	0.05	0.67
Minor Injury	0.24	0.22	0.02	1.27	3.38	4.45	0.02	0.13
Non-incapacitating Injury	0.44	0.00	0.02	0.87	2.80	1.00	0.02	0.13
Incapacitating Injury	0.20	0.02	0.00	0.38	0.93	0.22	0.00	0.04
Fatal	0.00	0.00	0.00	0.05	0.11	0.00	0.00	0.00
Total	1.27	1.51	0.05	4.87	13.55	13.87	0.09	0.96

Figures 9 and 10 show the proportion of crashes by severity. The percentage of PDO crashes and minor crashes for rear-end crashes is higher than the percentage of injury/fatal crashes.

Table 28: Number of crashes (per year) by crash type and severity

Severity \ Type		Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear -end	Head -on	Other
PDO	Number	0.35	1.27	0.02	2.29	6.31	8.20	0.05	0.67
	Percent	28.4	84.3	33.3	47.0	46.6	59.1	60.0	69.8
Injury & Fatal	Number	0.87	0.24	0.04	2.58	7.22	5.67	0.04	0.29
	Percent	68.6	15.7	66.7	53.0	53.3	40.9	40.0	30.2
Total Crashes		1.27	1.51	0.05	4.87	13.55	13.87	0.09	0.96

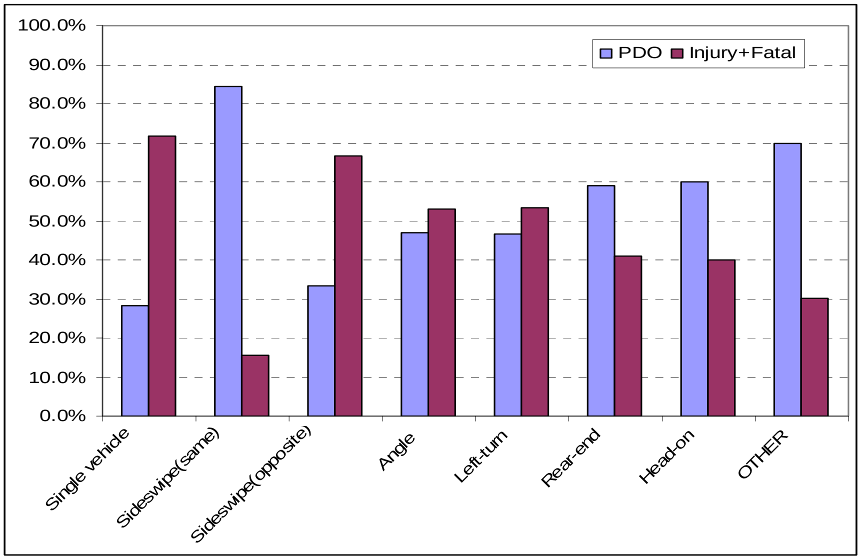

Figure 9: Percentage of crashes per year by crash type and severity (PDO vs. injury and fatal)

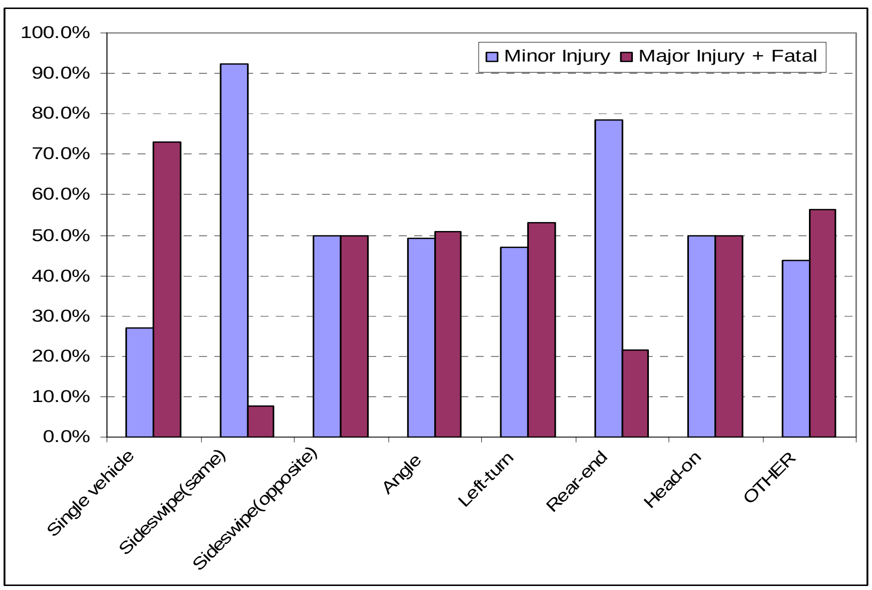

Figure 10: Percentage of crashes per year by crash type and severity (minor vs. major)

RLC Crashes at RLC Intersections

Using the criteria established previously to select RLC crashes, 1254 out of 1990 crashes are identified as RLC crashes. The summary statistics are:

- Duration of data: October 1, 1998 to September 9, 2003 (5 years)
- Number of RLC crashes: 1254 over 5 years
- Number of RLR crashes: 220 over 5 years
- Number of ARLR crashes: 1034 over 5 years

From inspection of Table 29, it can be seen that an average of 22.8 RLC crashes occur each year at RLC intersections, and the average number of ARLR crashes (18.8/year) is higher than that of RLR crashes (4.0/year) as was found previously.

Table 29: Mean value of RLC crashes by crash type

Crash Type / Mean	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear -end	Head-on	Other	Total
RLR	0.11	0	0	2.11	1.76	0	0	0.02	4.00
ARLR	0.11	0.51	0.02	1.11	9.31	7.40	0.07	0.27	18.80
RLC	0.22	0.51	0.02	3.22	11.07	7.40	0.07	0.29	22.80

Table 30: Mean value of RLC crashes by severity

	Unknown	No Injury	Minor Injury	Non-Incapacitating Injury	Incapacitating Injury	Fatal	Total
RLR	0	1.71	0.95	0.87	0.44	0.04	4.00
ARLR	0	9.51	5.49	2.93	0.78	0.09	18.80
RLC	0	11.22	6.44	3.80	1.22	0.13	22.80

Table 30 shows the average number of crashes per year by severity, while these values are presented differently in Tables 31 and 32. As was found previously, RLR crashes are generally more serious than ARLR crashes, evidenced by the proportion of major and fatal crashes associated with RLR crashes that is higher than the same proportion for ARLR associated crashes. Figures 11 and 12 also show that angle crashes are more serious than rear-end crashes.

Table 31: Number of crashes per year by severity (PDO vs. injury and fatal)

	Number		Percentage	
	PDO	INJURY+FATAL	PDO	INJURY+FATAL
RLR	1.71	2.29	42.7%	57.3%
Avoiding RLR	9.51	9.29	50.6%	49.4%
RLC TOTAL	11.22	11.58	49.2%	50.8%

Table 32: Number of crashes per year by severity (minor vs. major and fatal)

	Number		Percentage	
	Minor	Major + FATAL	Minor	Major + FATAL
RLR	0.95	1.35	41.3%	58.7%
Avoiding RLR	5.49	3.80	59.1%	40.9%
RLC TOTAL	6.44	5.15	55.6%	44.4%

Table 33: Number of crashes per year by crash type and severity

Type / Severity	Single Vehicle	Sideswipe (Same Direction)	Sideswipe (Opposite Direction)	Angle	Left Turn	Rear - end	Head-on	OTHER
Unknown	0	0	0	0	0	0	0	0
No Injury	0	0.44	0.02	1.44	4.84	4.33	0.04	0.13
Minor Injury	0.05	0.07	0	0.91	2.87	2.44	0.02	0.07
Non-incapacitating Injury	0.11	0	0	0.60	2.51	0.49	0.02	0.07
Incapacitating Injury	0.05	0	0	0.24	0.76	0.15	0	0.02
Fatal	0	0	0	0.04	0.09	0.00	0	0.00
Total	0.22	0.51	0.02	3.22	11.07	7.40	0.07	0.29

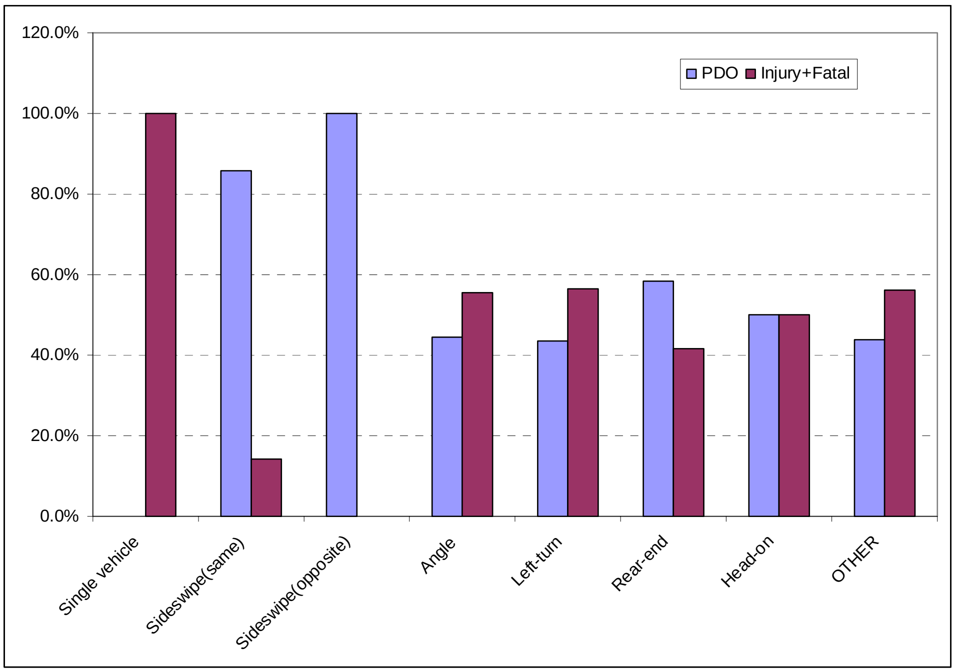

Figure 11: Percentage of crashes (per year) by crash type and severity (PDO vs. injury and fatal)

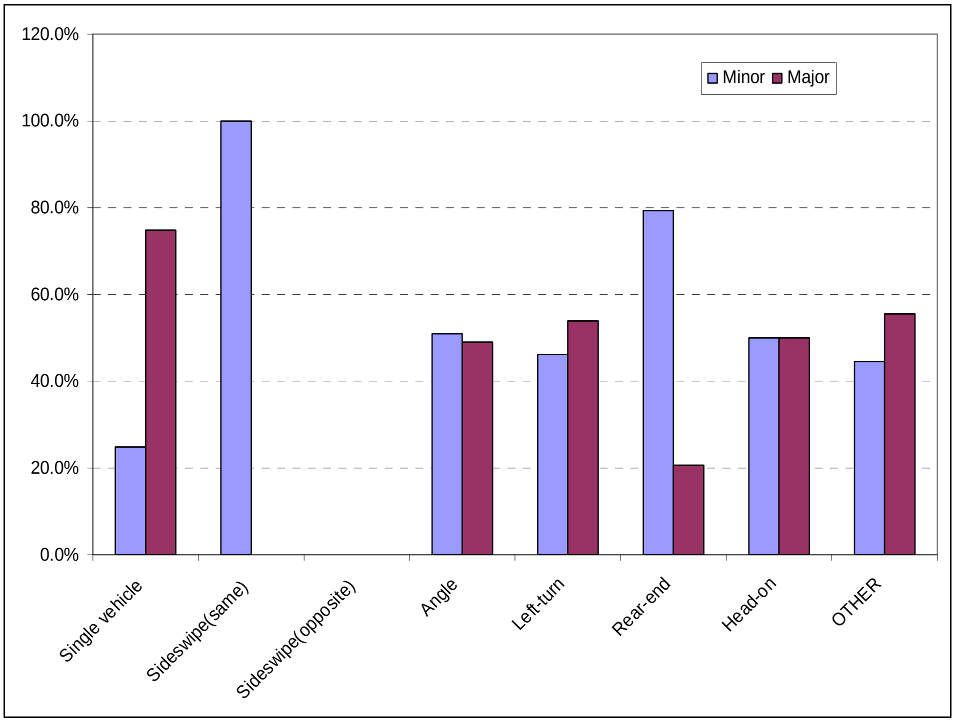

Figure 12: Percentage of crashes (per year) by crash type and severity (minor vs. major)

B. Traffic volume and Signal phasing data

The data extracted from the survey for site specifics and signal phasing are summarized, and are shown in Table 34.

Table 34: Traffic volume and signal phasing data

Intersection Name	Direction	ADT/VPH*	Date	# of lanes	Yellow Interval
40th St & Cactus Rd	NB	1230*	2002	2	-
	SB	1750*	2002	2	-
	EB	-	-	4	-
	WB	5020*	2002	4	-
51st Ave & Indian School Rd	NB	3340*	2002	3	-
	SB	2870*	2002	4	-
	EB	4380*	2002	4	-
	WB	4790*	2002	4	-
40th St & Bell Rd	NB	1600*	2002	3	-
	SB	1470*	2002	3	-
	EB	6420*	2002	4	-
	WB	4900*	2002	4	-
35th Ave & McDowell Rd	NB	-	-	3	-
	SB	-	-	3	-
	EB	15398	2001-09-05	3	-
	WB	-	-	3	-

Intersection Name	Direction	ADT/VPH*	Date	# of lanes	Yellow Interval
35th Ave & Dunlap Ave	NB	-	-	3	-
	SB	-	-	5	-
	EB	22256	2002-05-21	3	-
	WB	-	-	5	-
12th St & Indian School Rd	NB	3260*	2002	2	-
	SB	3180*	2002	2	-
	EB	4770*	2002	3	-
	WB	5360*	2002	3	-
7th Ave & Greenway Rd	NB	3970*	2002	2	-
	SB	3730*	2002	4	-
	EB	4270*	2002	4	-
	WB	3820*	2002	4	-
32nd St & McDowell Rd	NB	22130	2002-08-20	3	-
	SB	23367	2002-08-20	3	-
	EB	-	-	3	-
	WB	-	-	3	-
48th St & Ray Rd	NB	8930	2002-03-11	5	-
	SB	-	-	4	-
	EB	-	-	4	-
	WB	-	-	5	-
19th Ave & Thunderbird Rd	NB	3600*	2002	3	-
	SB	3440*	2002	3	-
	EB	4890*	2002	2	-
	WB	4210*	2002	3	-

III. Evaluation Methodologies and Results

In this chapter, the evaluation methodologies used in the study are described and the results of each methodology are represented. In this study, the following 4 methods were employed: simple before-and-after study, before-and-after study with comparison crashes, before-and-after study with traffic volume corrections, and the empirical Bayesian method for correcting possible regression to the mean. The use of four different analysis approaches allows for the assessment of the sensitivity of the results to analysis assumptions, and enables the inspection of consistency of results across methods.

Target Crashes and Target Approaches

As mentioned previously, the objective of this research is to evaluate the impact of red light cameras (RLCs) on safety. In order to evaluate the impact of RLCs on crash occurrence, it is necessary to understand which crash types are affected by RLCs—referred to as *target crashes*.

To identify target crashes, the three filter criteria discussed previously were applied:

1. Distance from crash occurrence location to the center of the intersection,
2. Drivers' physical condition (impaired drivers excluded)
3. Vehicles prior action

In addition, to filter target crashes, they are identified as target crashes when they are materially affected by the installation of a red light camera. For instance, if a red light camera were installed on the west bound approach of a 4-leg intersection and one rear-end crash occurred on the south bound approach, then that crash may not be directly affected by the installation of the red light camera—there is sufficient uncertainty to not identify this crash as a RLR crash. On the contrary, if the rear-end crash occurred on the west bound approach, it is more likely to be caused by the installation of a red light camera. Of course spillover effects are possible, however these effects are considered later in the analysis.

As a result *target approach crashes* are defined as crashes occurring on approaches equipped with RLCs. However, it is worthwhile to examine the crashes on the non-RLC approaches, since they could reflect the spillover effects of the RLCs on other approaches. That is, it is possible that the existence of a red light camera could affect driver behavior, thereby inducing more careful driving and less red light running. Using these definitions of target crashes and target approach crashes, the evaluations are performed.

Study Duration

The evaluation employs as long a study period for both before and after RLC installation as the data and resources allow (McGee and Eccles, 2003). This recommendation is relevant for considering regression-to-the-mean effects as well as for sample size considerations. The duration of data available for the analysis is

- Phoenix: October 1998 ~ September 2003
- Scottsdale: January 1990 ~ December 2003

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 $500 to $1000). Table 35 shows the study duration for each intersection in the study.

Table 35: Study duration for each intersection

Jurisdiction	Intersection Name	Before period (year)	After period (year)
Phoenix	40th St & Cactus Rd	2.92	2.08
	51st Ave & Indian School Rd	2.92	2.08
	40th St & Bell Rd	3.00	2.00
	35th Ave & McDowell Rd	3.00	2.00
	35th Ave & Dunlap Ave	3.08	1.92
	12th St & Indian School Rd	3.08	1.92
	7th Ave & Greenway Rd	3.17	1.83
	32nd St & McDowell Rd	3.17	1.83
	48th St & Ray Rd	3.17	1.83
	19th Ave & Thunderbird Rd	3.17	1.83
	7th St & Bell Rd	-	-
Scottsdale	68th Street & Camelback	5.92	7.75
	Scottsdale & McDowell	5.92	7.75
	Scottsdale & Doubletree	5.92	7.75
	Scottsdale & Shea	5.92	7.75
	Hayden & McDonald	5.92	7.75
	Hayden & McDowell	5.92	7.75
	Hayden & Shea	5.92	7.75
	Scottsdale & Mercer	5.92	7.75
	Scottsdale & Thomas	10.08	3.58
	Scottsdale & Cactus	10.75	2.92
	Hayden & Indian School	10.83	2.83
	Pima & Pinnacle Peak	12.08	1.58
	Hayden & McCormick	12.25	1.42
	Scottsdale & Frank Lloyd Wright	12.33	1.33

Basic Concepts of a 4-Step Before-After Study

In this section, the basic concepts of a before-and-after study are described, and the basic 4-step procedure for estimating the effects of RLCs is also provided. Some derivations are provided to support the analysis steps. The 4-step process is used throughout the analysis procedure, with enhancements, to form the basis of the analysis methodology.

The key objective of the before-and-after study is to estimate the change of safety as a result of the treatment. In general, the safety in the before period is measured by the expected number of crashes at the site, while the safety in after period is λ, and is given by

π = The expected number of crashes in the after period if the treatment had not been installed,

λ = The observed number of crashes in the after period with the treatment in place.

Using these safety indexes, the effectiveness of the treatment is estimated by

$\delta = \pi - \lambda$ = Change in safety due to the treatment

$\theta = \lambda / \pi$ = Index of effectiveness of the treatment

If δ is greater than 1 and θ is less than 1, then we can conclude the treatment is effective. For example, a θ of 0.75 indicates an estimated 25% reduction in target crashes due to the treatment. The parameters π, λ, δ, and θ are unknown parameters and must be estimated using the available data. There are numerous “tricky” aspects of estimating these unknown parameters, as is discussed in the following sections.

Intuitively, the value of λ is 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 —the expected number of crashes in the after period in the absence of treatment. However, it is naïve to predict the value of π using the observed number of crashes in the before period. This is because there are potentially many factors which may have changed from the before to the after period, such as traffic volumes, weather, crash reporting thresholds, the probability of reporting, the driving population, and so on. In the strictest sense, the observed number of crashes in the before period represents the safety in the after period only if all safety related factors are constant across the two periods, save for the treatment. Because often this assumption is unrealistic, the simple before-and-after approach is called naïve, and often more rigorous evaluation methodologies are needed to obtain accurate estimates of π .

No matter what corrections are made to the naïve before-and-after study, a basic 4-step procedure is used (with modifications) to estimate the safety effect of a treatment. For the simple or naïve before-and-after study approach, the 4-step procedure is described as follows.

Figure 13 depicts the hypothetical target crashes data for a simple before-and-after study. In this example, the duration of the before and after data are from a period of 5 years, and k_i and l_i represent the observed number of target crashes in the before and after periods respectively. Our goal is to predict π, which is sum of π_i's, by using the k_i's, the count of crashes in the before period.

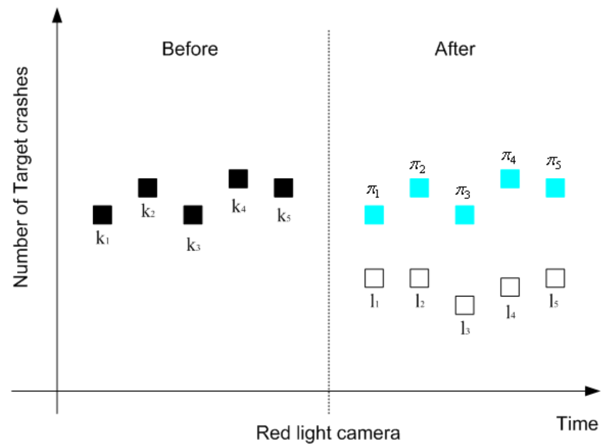

Figure 13: Illustration of a simple or naïve before-after study

Step 1: Estimate λ and predict π

The first step is to estimate λ and π. As mentioned previously, the estimate of λ is equal to the sum of the observed number of crashes in the after period. Also, the predicted value of π is equal to the sum of the observed number of crashes in the before period. In the simple before-and-after study, these estimates are obtained using

$$\hat{\lambda} = \sum_{i=1}^{5} l_i = L \text{, it means } E[\hat{\lambda}] = E[L] = \lambda$$

$$\hat{\pi} = \sum_{i=1}^{5} k_i = K \text{, it means } E[\hat{\pi}] = E[K] = \pi$$

Step 2: Estimate $\hat{\sigma}^2[\hat{\lambda}]$ and $\hat{\sigma}^2[\hat{\pi}]$

The second step is to estimate the variance of $\hat{\lambda}$ and $\hat{\pi}$. Suppose that the number of target crashes is Poisson distributed (which is often the case at a single site), then the variance is equal to the mean.

$$\hat{\sigma}^2[\hat{\lambda}] = \sigma^2[\hat{\lambda}] = E[\hat{\lambda}] = \lambda$$

$$\hat{\sigma}^2[\hat{\pi}] = \sigma^2[\hat{\pi}] = E[\hat{\pi}] = \pi$$

Of course, however, the estimate of variance of $\hat{\pi}$ will depend on the method chosen to consider various factors.

Step 3: Estimate δ and θ

The estimates of treatment effectiveness, δ and θ, are now estimated using

$$\hat{\delta} = \hat{\pi} - \hat{\lambda} = K - L \text{, which derives from } E[\hat{\delta}] = E[\hat{\pi} - \hat{\lambda}] = E[\hat{\pi}] - E[\hat{\lambda}] = \pi - \lambda .$$

That is, the estimator $\hat{\delta}$ is an unbiased estimator of δ. However, the estimator $\hat{\theta}^* = \dfrac{\hat{\lambda}}{\hat{\pi}}$ is not an unbiased estimator for θ for small samples (it as asymptotically unbiased though), or

$$E[\hat{\theta}^*] = E\left[\frac{\hat{\lambda}}{\hat{\pi}}\right] \neq \frac{\lambda}{\pi} = \theta .$$

Thus, an unbiased estimator of θ is needed because unbiased estimators are generally preferred to biased estimators of parameters, even though there are rare cases when biased estimators are preferred because they result in estimators with smaller standard errors.

The fact that $\hat{\theta}^*$ is a biased estimator can be proven by the delta method with Taylor series expansion. Statistically, in a case where g(X, Y) is very complicated or is a non-linear function of random variables, the expectation and variance of g(X, Y) can be approximately computed using the delta method.

Suppose that random variable Z is the function of random variable X, Y and $\mu = (\mu_X, \mu_Y)$, then Z can be rewritten by Taylor series as follows:

$$Z = g(X,Y) = g(\mu) + (X - \mu_X)\frac{\partial g}{\partial x}(\mu) + (Y - \mu_Y)\frac{\partial g}{\partial y}(\mu)$$
$$+ \frac{1}{2}(X - \mu_X)^2 \frac{\partial^2 g}{\partial x^2}(\mu) + \frac{1}{2}(Y - \mu_Y)^2 \frac{\partial^2 g}{\partial y^2}(\mu) + R$$

where R is the remainder. From the properties of expectation:

$$E[Z] = E[g(\mu)] + E[(X - \mu_X)]\frac{\partial g}{\partial x}(\mu) + E[(Y - \mu_Y)]\frac{\partial g}{\partial y}(\mu)$$
$$+ \frac{1}{2}\mathrm{E}[(X - \mu_X)^2]\frac{\partial^2 g}{\partial x^2}(\mu) + \frac{1}{2}\mathrm{E}[(Y - \mu_Y)^2]\frac{\partial^2 g}{\partial y^2}(\mu) + E[R]$$
$$\cong g(\mu) + \frac{1}{2} \cdot \sigma_X{}^2 \cdot \frac{\partial^2 g}{\partial x^2}(\mu) + \frac{1}{2} \cdot \sigma_Y{}^2 \cdot \frac{\partial^2 g}{\partial y^2}(\mu)$$

Again, from the properties of variance:

$$VAR[Z] = VAR\left[g(\mu)\right] + VAR\left[(X-\mu_X)\frac{\partial g}{\partial x}(\mu)\right] + VAR\left[(Y-\mu_Y)\frac{\partial g}{\partial y}(\mu)\right] + VAR[R']$$
$$\cong \sigma_X^2 \cdot \left[\frac{\partial g}{\partial x}(\mu)\right]^2 + \sigma_Y^2 \cdot \left[\frac{\partial g}{\partial y}(\mu)\right]^2$$

Equivalently, let $\hat{\theta}^* = \dfrac{\hat{\lambda}}{\hat{\pi}}$ be Z, and then

$$E[\hat{\theta}^*] \cong \frac{\lambda}{\pi} + \frac{1}{2} \cdot \sigma_\lambda^2 \cdot 0 + \frac{1}{2} \cdot \sigma_\pi^2 \cdot 2\lambda\pi^{-3}$$
$$= \frac{\lambda}{\pi} + \frac{\sigma_\pi^2}{\pi^3} = \frac{\lambda}{\pi} \cdot \left[1 + \frac{\sigma_\pi^2}{\pi^2}\right] \neq \frac{\lambda}{\pi}$$

Thus, an unbiased estimator of θ is defined as follows:

$$\hat{\theta} \cong \frac{\left(\dfrac{\hat{\lambda}}{\hat{\pi}}\right)}{\left(1 + \dfrac{VAR[\hat{\pi}]}{\hat{\pi}^2}\right)} = \frac{\left(\dfrac{L}{K}\right)}{\left(1 + \dfrac{K}{K^2}\right)}$$

Step 4: Estimate $\hat{\sigma}^2[\hat{\delta}]$ *and* $\hat{\sigma}^2[\hat{\theta}]$

The final step is to estimate the variance of $\hat{\delta}$ and $\hat{\theta}$. The estimate of the variance of $\hat{\delta}$ is

$$\hat{\sigma}^2[\hat{\delta}] = \hat{\sigma}^2[\hat{\pi} - \hat{\lambda}] = \hat{\sigma}^2[\hat{\pi}] + \hat{\sigma}^2[\hat{\lambda}]$$
$$= \hat{\pi} + \hat{\lambda} = K + L$$

In order to obtain the estimate of the variance of unbiased estimator $\hat{\theta}$, the variance of biased estimator $\hat{\theta}^*$ is examined,

$$VAR[\hat{\theta}^*] \cong \sigma_\lambda^2 \cdot \left[\frac{1}{\pi}\right]^2 + \sigma_\pi^2 \cdot \left[\frac{-\lambda}{\pi^2}\right]^2$$
$$= \left[\frac{\sigma_\lambda^2 \cdot \lambda^2}{\pi^2 \cdot \lambda^2}\right] + \left[\frac{\sigma_\pi^2 \cdot \lambda^2}{\pi^4}\right]$$
$$= \theta^2 \cdot \left[\frac{\sigma_\lambda^2}{\lambda^2} + \frac{\sigma_\pi^2}{\pi^2}\right]$$

Thus, the estimate of the variance of $\hat{\theta}$ is

$$\hat{\sigma}^2[\hat{\theta}] \cong \frac{\hat{\theta}^2 \cdot \left[\frac{\widehat{VAR}(\hat{\lambda})}{\hat{\lambda}^2} + \frac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^2} \right]}{\left[1 + \frac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^2} \right]^2} = \frac{\hat{\theta}^2 \cdot \left[\frac{L}{L^2} + \frac{K}{K^2} \right]}{\left[1 + \frac{K}{K^2} \right]^2}$$

Using these 4-steps, the magnitude of effectiveness ($\hat{\delta}, \hat{\theta}$) and their variances are obtained. Using estimates $\hat{\delta}$ and $\hat{\theta}$ to measure effect size and index of effectiveness of the treatment, their variances can be used to approximate the "levels of confidence" of the results. Table 36 shows the goal and formulas for each of the four steps in a simple before-and-after study.

Table 36: The basic formulas for simple before-after study in 4-step procedure

Step	Goals	Formulas for simple before-and-after study
Step 1	Estimate λ and predict π	$\hat{\lambda} = L$ $\hat{\pi} = K$
Step 2	Estimate $\hat{\sigma}^2[\hat{\lambda}]$ and $\hat{\sigma}^2[\hat{\pi}]$	$\hat{\sigma}^2[\hat{\lambda}] = \hat{\lambda}$ $\hat{\sigma}^2[\hat{\pi}] = \hat{\pi}$
Step 3	Estimate δ and θ	$\hat{\delta} = \hat{\pi} - \hat{\lambda} = K - L$ $\hat{\theta} \cong \frac{\left(\frac{\hat{\lambda}}{\hat{\pi}}\right)}{\left(1 + \frac{\widehat{VAR}[\hat{\pi}]}{\hat{\pi}^2}\right)} = \frac{\left(\frac{L}{K}\right)}{\left(1 + \frac{K}{K^2}\right)}$
Step 4	Estimate $\hat{\sigma}^2[\hat{\delta}]$ and $\hat{\sigma}^2[\hat{\theta}]$	$\hat{\sigma}^2[\hat{\delta}] = \hat{\pi} + \hat{\lambda} = K + L$ $\hat{\sigma}^2[\hat{\theta}] \cong \frac{\hat{\theta}^2 \cdot \left[\frac{\widehat{VAR}(\hat{\lambda})}{\hat{\lambda}^2} + \frac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^2} \right]}{\left[1 + \frac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^2} \right]^2} = \frac{\hat{\theta}^2 \cdot \left[\frac{L}{L^2} + \frac{K}{K^2} \right]}{\left[1 + \frac{K}{K^2} \right]^2}$

Analysis Method 1: Simple or Naïve Before-After Study with Ratio of Durations

The first analysis method employed uses the naïve before-and-after study with a correction made for ratio of durations. That is, the analysis recognizes that the duration of time may not be the same from before to after periods. The analysis makes the following assumptions:

Assumption 1: Traffic volume, geometry, road user behavior, weather, and many other factors have not changed from the before to the after periods. In other words, both recognized factors and unrecognized factors are the same in both periods.

Assumption 2: There are no treatments or improvements other than the installation of red light cameras in the after period.

Assumption 3: The probability that the crashes are reported is the same in both periods and the reporting threshold has not changed.

Although these assumptions may be questionable at some or many sites, they serve as a starting point for the analysis, and provide results that may serve as a baseline.

Ratio of duration

Basically, the study duration of crash history varies across the intersections. The ratio of durations, r_d, is used to modify the 4-step process by including the term:

$$r_d(i) = \frac{\text{Duration of after period for entity i}}{\text{Duration of before period for entity i}}$$

Prediction in simple before-after study with ratio of duration

When the ratio of duration is considered, the prediction value ($\hat{\pi}$) is

$$\hat{\pi} = \sum_{i=1}^{n} r_d(i) \cdot K_i \ .$$

Where, K_i is the observed number of target crashes in the before period for intersection i and n is number of intersections for the study. Thus, the estimate of variance for $\hat{\pi}$ is

$$VAR[\hat{\pi}] = \sum_{i=1}^{n} \left[r_d(i)\right]^2 \cdot K_i \ .$$

With the change of $\hat{\pi}$ and $\hat{V}AR[\hat{\pi}]$, the remaining steps follow the four step procedure described previously.

Table 37 shows the observed number of crashes in the before period (K), the predicted number of crashes in the after period ($\hat{\pi}$), and the estimated number of crashes in the after period ($\hat{\lambda}$). In addition, the results in Table 37 include the number of crashes (K, $\hat{\pi}$, and $\hat{\lambda}$) on target approaches. A target approach is the approach whose operations are materially affected by the installation of a red light camera. Crash types are divided into angle, left-turn, rear-end, and total.

Table 37: The number of crashes in the simple before-after study

	Jurisdiction	Crash Types	K	$\hat{\pi}$	$\hat{\lambda}$
All Approaches	Phoenix	Angle Crashes	97	61.3	56
		Left-turn Crashes	335	213.4	226
		Rear-end Crashes	201	127.5	162
		Total	633	402.2	444
	Scottsdale	Angle Crashes	207	162.6	113
		Left-turn Crashes	457	281.4	167
		Rear-end Crashes	676	397.3	590
		Total	1340	841.2	870
Target Approach	Phoenix	Angle Crashes	50.0	32.1	20.0
		Left-turn Crashes	197.0	126.2	122.0
		Rear-end Crashes	81.0	51.8	83.0
		Total	328.0	210.1	225.0
	Scottsdale	Angle Crashes	91	76.8	62
		Left-turn Crashes	308	202.7	106
		Rear-end Crashes	199	116.5	184
		Total	598	396.0	352

Analysis Results: Change in safety and index of effectiveness

With the predicted value ($\hat{\pi}$) and the estimate for variance of $\hat{\pi}$ (e.g. $\hat{V}AR[\hat{\pi}]$), the change in safety ($\hat{\delta}$) and index of effectiveness ($\hat{\theta}$) are calculated. Tables 38 and 39 show these results with standard deviations.

Table 38: Results of the simple before-after study (all approaches)

Jurisdiction	Crash Types	Change in Safety		Index of Effectiveness	
		$\hat{\delta}$	$S[\hat{\delta}]$	$\hat{\theta}$	$S[\hat{\theta}]$
Phoenix	Angle Crashes	5.28	9.74	0.90	0.15
	Left-turn Crashes	-12.56	19.05	1.06	0.09
	Rear-end Crashes	-34.52	15.60	1.26	0.13
	All Crashes	-41.80	26.48	1.10	0.07
Scottsdale	Angle Crashes	49.59	17.35	0.69	0.09
	Left-turn Crashes	114.41	21.54	0.59	0.06
	Rear-end Crashes	-192.75	31.52	1.48	0.10
	All Crashes	-28.75	41.94	1.03	0.05

Table 39: Results of the simple before-after study (target approaches)

Jurisdiction	Crash Types	Change in Safety		Index of Effectiveness	
		$\hat{\delta}$	$S[\hat{\delta}]$	$\hat{\theta}$	$S[\hat{\theta}]$
Phoenix	Angle Crashes	12.09	6.38	0.61	0.16
	Left-turn Crashes	4.19	14.26	0.96	0.11
	Rear-end Crashes	-31.19	10.79	1.58	0.24
	All Crashes	-14.91	18.99	1.07	0.09
Scottsdale	Angle Crashes	14.76	12.37	0.80	0.14
	Left-turn Crashes	96.73	18.06	0.52	0.06
	Rear-end Crashes	-67.50	17.40	1.57	0.18
	All Crashes	43.99	27.96	0.89	0.07

Figures 14 and 15 provide estimates of the interval of the index of effectiveness ($\hat{\theta} \pm 1.96 S(\hat{\theta})$) as approximated by a 95% confidence interval. In all approaches, the installation of RLCs increased the number of rear-end crashes apparently, while it brought about a reduction of angle crashes. The results are more significant in Scottsdale than in Phoenix. In Phoenix it is possible that the installation of RLCs has adverse effects on angle crashes and left-turn crashes because the approximate 95% confidence interval for these crash types includes the value 1, even though the expected effectiveness is below 1 for these crash types.

In Scottsdale, the observed effects of RLCs on angle crashes are less on target approaches (0.80) compared to all approaches (0.69). There is also greater uncertainty on all approaches than on target approaches of the estimated effects.

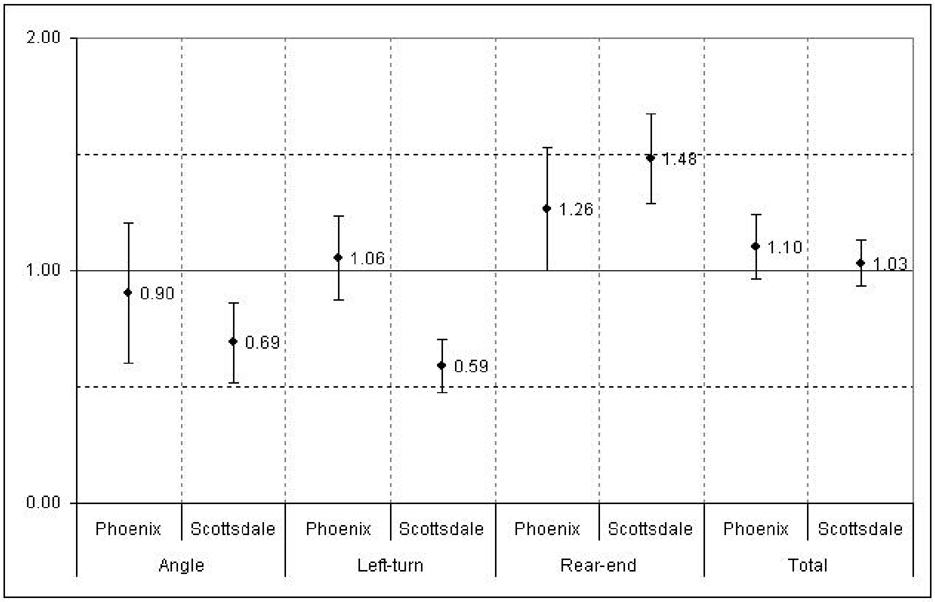

Figure 14: 95% CIs of index of effectiveness (naïve method, all approaches)

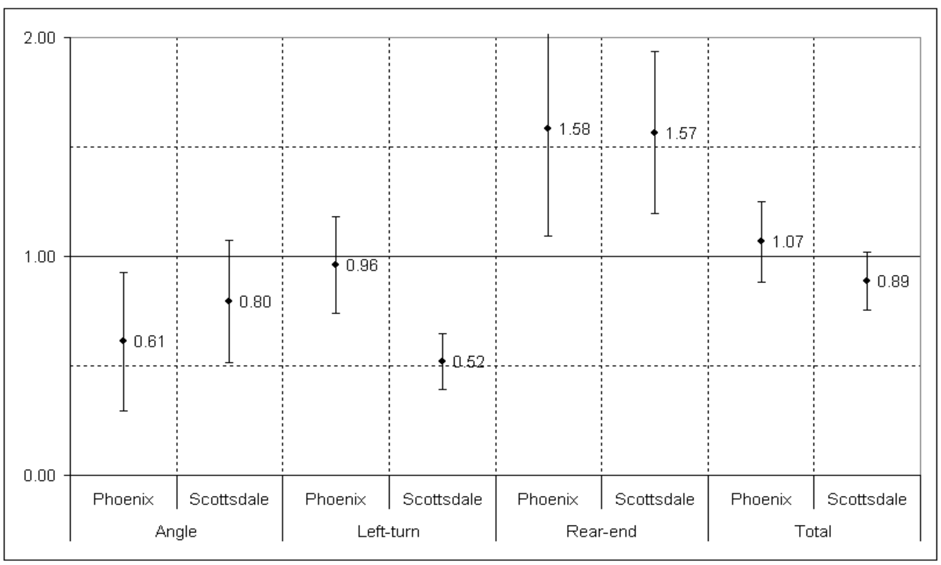

Figure 15: 95% CIs of indexes of effectiveness (naïve method, target approaches)

Analysis Method 2: Before-After Study with Correction for Traffic Flow

The naïve before-and-after study assumes that no changes other than the treatment have occurred from the before to the after periods. Of course numerous factors may influence safety, such as changes in traffic volumes, geometry, signage, striping, weather, surrounding land uses, and driving populations. These factors can be divided into two categories: recognized and unrecognized factors. The recognized factors are measurable, while unrecognized factors are not measurable. Thus, the recognized factors can be modeled directly, while unrecognized factors cannot be modeled directly (only indirectly).

In analysis method 2, the impact of red light cameras on safety is adjusted by considering the change of traffic flow from the before to the after periods. As stated previously, traffic volumes are extremely influential on safety, and should ideally be considered—especially for relatively long periods of observation. Due to data availability, adjustments to the 4-step process are considered for traffic volumes in Scottsdale only.

Correction in 4-step for the correction of traffic flow

To account for changes in traffic volumes, some of equations in the basic 4-step procedure need to be adjusted. Following are the adjustments needed to account for exposure, or traffic volumes, in the 4-step process.

Step 1: Estimate λ and predict π

The estimate of λ is equal to the sum of the observed number of crashes in the after period,

$$\hat{\lambda} = \sum_{i=1}^{5} l_i = L \,.$$

However, the estimate of π is not K if traffic volume is considered. This is because the relationship between safety and traffic volumes must be considered. Let r_{tf} be the ratio of traffic flow in the before period to that in the after period. Then, the estimate of π is expressed as:

$$\hat{\pi} = \hat{r}_{tf} \cdot K$$

If the relationship between traffic flow and safety is proportional, the ratio of traffic flow can be expressed by

$$\hat{r}_{tf} = \frac{A_{avg}}{B_{avg}}$$

In this equation, $\tilde{A}_{avg}$ and $\tilde{B}_{avg}$ represent the expected traffic volume during the after and before periods respectively. However, the relationship between traffic flow and safety is not typically proportional in the real world, and the relationship needs to be considered more carefully. Generally, the relationship between traffic flow and safety is represented by a Safety Performance Function (SPF)—a functional relationship between traffic volumes and safety for a specific site or class of sites (the development of SPFs for Scottsdale is described in the next section). Thus, we can describe the relationship using SPFs. If SPFs are employed as a ratio of traffic flows, then r_{tf} is a combination of SPFs,

$$\hat{r}_{tf} = \frac{f\left(\tilde{A}_{avg}\right)}{f\left(\tilde{B}_{avg}\right)}.$$

Then, the estimate of π can be expressed as follows:

$$\hat{\pi} = \frac{f\left(\tilde{A}_{avg}\right)}{f\left(\tilde{B}_{avg}\right)} \cdot K .$$

Step 2: Estimate $\hat{\sigma}^2[\hat{\lambda}]$ and $\hat{\sigma}^2[\hat{\pi}]$

From the property of Poisson distribution, the variance is equal to the mean, thus, the estimate of variance for $\hat{\lambda}$ is L.

Using the delta method, the estimate of variance for $\hat{\pi}$ is approximated as follows:

$$\widetilde{VAR}[\hat{\pi}] \cong \hat{r}_{tf}^{\,2} \cdot \widetilde{VAR}[K] + K^2 \cdot \widetilde{VAR}[\hat{r}_{tf}]$$

If a SPF is employed to describe the relationship between traffic flow and safety, the estimate of variance for $\hat{r}_{tf}$ is

$$\begin{aligned}
\widetilde{VAR}[\hat{r}_{tf}] &= \widetilde{VAR}\left[\frac{f\left(\tilde{A}_{avg}\right)}{f\left(\tilde{B}_{avg}\right)}\right] \\
&\cong \widetilde{VAR}[f\left(\tilde{A}_{avg}\right)] \cdot \left(\frac{\partial \hat{r}_{tf}}{\partial f\left(\tilde{A}_{avg}\right)}\right)^2 + \widetilde{VAR}[f\left(\tilde{B}_{avg}\right)] \cdot \left(\frac{\partial \hat{r}_{tf}}{\partial f\left(\tilde{B}_{avg}\right)}\right)^2 \\
&= \widetilde{VAR}[f\left(\tilde{A}_{avg}\right)] \cdot \left(\frac{1}{f^2\left(\tilde{B}_{avg}\right)}\right) + \widetilde{VAR}[f\left(\tilde{B}_{avg}\right)] \cdot \left(\frac{f^2\left(\tilde{A}_{avg}\right)}{f^4\left(\tilde{B}_{avg}\right)}\right)
\end{aligned}$$

Thus, the estimate of variance for $\hat{r}_{tf}$ can be rearranged as follows:

$$\widehat{VAR}[\hat{r}_{tf}] \cong \hat{r}_{tf}^{\,2} \cdot \left(\frac{\widehat{VAR}\left[f\left(\hat{A}_{avg}\right)\right]}{f^{2}\left(\hat{A}_{avg}\right)} + \frac{\widehat{VAR}\left[f\left(\hat{B}_{avg}\right)\right]}{f^{2}\left(\hat{B}_{avg}\right)} \right)$$

Using the delta method again, the variance of the expected number of accidents in both periods is obtained using

$$\widehat{VAR}\left[f\left(\hat{A}_{avg}\right)\right] \cong \widehat{VAR}[\hat{A}_{avg}] \cdot \left(\frac{\partial f\left(\hat{A}_{avg}\right)}{\partial \hat{A}_{avg}} \right)^{2}$$

$$\widehat{VAR}\left[f\left(\hat{B}_{avg}\right)\right] \cong \widehat{VAR}[\hat{B}_{avg}] \cdot \left(\frac{\partial f\left(\hat{B}_{avg}\right)}{\partial \hat{B}_{avg}} \right)^{2}$$

With these corrections, the remaining steps (step 3 and step 4) are as described previously.

Step 3: Estimate δ and θ

The estimate of δ and θ is

$$\hat{\delta} = \hat{\pi} - \hat{\lambda}\,, \;\; \hat{\theta} \cong \frac{\left(\dfrac{\hat{\lambda}}{\hat{\pi}}\right)}{\left(1 + \dfrac{\widehat{VAR}[\hat{\pi}]}{\hat{\pi}^{2}}\right)}$$

Step 4: Estimate $\hat{\sigma}^{2}[\hat{\delta}]$ and $\hat{\sigma}^{2}[\hat{\theta}]$

The estimate of the variance of $\hat{\delta}$ and $\hat{\theta}$ is

$$\widehat{VAR}[\hat{\delta}] = \hat{\pi} + \hat{\lambda}$$

$$\widehat{VAR}[\hat{\theta}] \cong \frac{\hat{\theta}^{2} \cdot \left[\dfrac{\widehat{VAR}(\hat{\lambda})}{\hat{\lambda}^{2}} + \dfrac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^{2}} \right]}{\left[1 + \dfrac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^{2}} \right]^{2}}$$

Developing SPFs for predicting the safety effects of changes in traffic volumes

As mentioned previously, the single best predictor of crashes is traffic volume. The simple before-and-after studies ignored changes in traffic volumes from the before to the after periods, implying that traffic volumes remained constant. Often this is not the case, and the relationship between traffic volume and crashes must be taken into account. A key correction described in this section is the ratio of traffic flow (r_{tf}) which represents the expected change in safety from the before to the after periods. As described previously, SPFs are employed to obtain r_{tf} and are obtained from the relationship between traffic volumes and crashes. Thus, this section describes the derivation of the SPFs. Four subsections are provided: data description, modeling approach, comparing models, and modeling results.

Data Description

For modeling SPFs, the number of crashes and daily traffic data in the before period are used. Tables 40 and 41 show the summary of statistics for these crashes and AADT. In these tables, the number of observation (n) is not the number of intersections independent spatially but the number of intersections independent temporally. As a result, an intersection may produce several data points.

Table 40: Summary of statistics for crashes and AADT (target approaches)

Variable		Mean	Std. Dev.	Min	Max	Sum
Crash Types	Angle	0.73	0.87	0.00	4.00	35.00
	Left-turn	2.40	2.54	0.00	12.00	115.00
	Rear-end	1.92	2.13	0.00	9.00	92.00
	Total	5.04	3.48	1.00	16.00	242.00
Severities	Fatality	0.04	0.20	0.00	1.00	2.00
	Incapacitating Injury	0.50	0.74	0.00	3.00	24.00
	Non-incapacitating Injury	0.69	1.32	0.00	7.00	33.00
	Possible Injury	0.88	1.06	0.00	4.00	42.00
	PDO	2.92	2.02	0.00	8.00	140.00
AADT		72,879	22,098	16,661	104,827	3,498,169
$AADT_t$		22,103	7,096	5,706	35,363	1,060,957
$AADT_o$		22,624	7,638	4,731	39,038	1,085,931
$AADT_c$		28,152	12,456	6,224	51,046	1,351,280

Note: n=48

In Table 40 the summary statistics are divided into crash types and severity, and AADT is disaggregated into $AADT_t$, $AADT_o$, and $AADT_c$ for AADT on target approaches, AADT on opposing approaches, and AADT on perpendicular approaches respectively. For example, if a red light camera was installed on a northbound approach, then $AADT_t$ is the AADT on the northbound approach, $AADT_o$ is the AADT on the southbound approach, and $AADT_c$ is the sum of AADT on the east and westbound approaches.

Table 41: Summary of statistics for crashes and AADT (all approaches)

	Variable	Mean	Std. Dev.	Min	Max	Sum
Crash Types	Angle	1.47	1.23	0.00	5.00	72.00
	Left-turn	3.76	3.28	0.00	15.00	184.00
	Rear-end	6.37	4.69	0.00	17.00	312.00
	Total	11.59	6.07	2.00	25.00	568.00
Severities	Fatality	0.04	0.20	0.00	1.00	2.00
	Incapacitating Injury	0.80	0.98	0.00	3.00	39.00
	Non-incapacitating Injury	1.10	1.45	0.00	7.00	54.00
	Possible Injury	2.12	1.69	0.00	6.00	104.00
	PDO	7.47	4.26	1.00	18.00	366.00
AADT		73,027	21,891	16,661	104,827	3,578,330
$AADT_{maj}$		44,853	14,199	10,437	70,927	2,197,788
$AADT_{min}$		28,152	12,247	6,224	51,046	1,379,431

Note: n=49

With respect to all approaches, the AADT is divided into $AADT_{maj}$ and $AADT_{min}$, where $AADT_{maj}$ is the AADT on the major road and $AADT_{min}$ is the AADT on the minor road.

Modeling Approaches

The general approach used to develop SPFs involves the use of count-based models. Count variables indicate the number of times that an event has occurred (Long, 1997). The number of crashes observed at an intersection per year is a non-negative integer and serves as a count. A common mistake is to model count data as continuous data by applying standard least squares regression. This is not strictly correct because regression models yield predicted values that are non-integers and can also predict values that are negative, both of which are inconsistent with count data. These limitations make standard regression analysis inappropriate for modeling count data without modifying the dependent variables. Count data are properly modeled using a number of methods, the most popular of which are Poisson and negative binomial regression models (Washington *et al.*, 2003).

In a Poisson regression model, the probability of intersection i having y_i crashes per year (where y_i is a non-negative integer) is given by

$$P(y_i) = \frac{\lambda_i^{y_i} e^{-\lambda_i}}{y_i!} \qquad [1]$$

where $P(y_i)$ is the probability of intersection i having y_i crashes per year, and λ_i is the expected number of accidents per year at intersection i. Poisson regression models are estimated by specifying the Poisson parameter λ_i (the expected number of crashes per year) as a function of dependent variables.

For the intersection crashes example, dependent variables might include the traffic volume of the intersections, their geometric conditions, signalization, pavement types, visibility, and so on. The most common relationship between the independent variables ($\mathbf{x}$) and accidents is the log-linear model,

$$E[y_i \mid \mathbf{x}_i] = \lambda_i = \exp(\mathbf{x}_i\boldsymbol{\beta}) \qquad [2]$$

This specification (Equation [2]) is called the exponential mean function. The model comprising the Poisson probability distribution and the exponential mean function is typically referred to as the Poisson regression model, although more precisely it is the Poisson regression model with exponential mean function (Cameron and Trivedi, 1998).

This model is estimable by standard maximum likelihood methods, with the likelihood function given as

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{n} \frac{\lambda_i^{y_i}\, \mathrm{e}^{-\lambda_i}}{y_i\,!} = \prod_{i=1}^{n} \frac{\exp(\mathbf{x}_i\boldsymbol{\beta})^{y_i}\, \exp(-\exp(\mathbf{x}_i\boldsymbol{\beta}))}{y_i\,!}$$

The log of the likelihood function is simpler to manipulate and more appropriate for estimation,

$$LL(\boldsymbol{\beta}) = \sum_{i=1}^{n} [-\exp(\mathbf{x}_i\boldsymbol{\beta}) + y_i\mathbf{x}_i\boldsymbol{\beta} - \ln(y_i\,!)]$$

By maximizing this log-likelihood function for $\boldsymbol{\beta}$, an estimate of $\boldsymbol{\beta}$ is obtained. These maximum likelihood estimates ($\hat{\boldsymbol{\beta}}$) produce parameters that are consistent, asymptotically normal, and asymptotically efficient. Thus, the Poisson regression model is used to model SPFs, using traffic volumes as the independent variable.

However, the Poisson regression model rarely fits in practice since the conditional variance is greater than the conditional mean in many applications. If this equality ($E[y_i] = VAR[y_i]$), which is assumed in the Poisson regression model, does not hold, the data are said to be under dispersed ($E[y_i] > VAR[y_i]$) or over dispersed ($E[y_i] < VAR[y_i]$).

To overcome the over-dispersion problem, the negative binomial model is often employed. In the negative binomial regression model, the conditional mean can be expressed as follows:

$$\tilde{\lambda}_i = \exp(\mathbf{x}_i\boldsymbol{\beta} + \varepsilon_i) \qquad [3]$$

where $\exp(\varepsilon_i)$ is a random error. The relationship between $\tilde{\lambda}_i$ and λ_i of the Poisson regression model is

$$\tilde{\lambda}_i = \exp(\mathbf{x}_i\boldsymbol{\beta}) \cdot \exp(\varepsilon_i) = \lambda_i \cdot \exp(\varepsilon_i)$$

The most common implementation of $\exp(\varepsilon_i)$ is that $\exp(\varepsilon_i)$ is a gamma-distributed error term with mean 1 and variance α. Thus, the expected value of y for the negative binomial distribution is the same as for the Poisson distribution:

$$E[y_i \mid \mathbf{x}_i] = \lambda_i = \exp(\mathbf{x}_i\boldsymbol{\beta}) \qquad [4]$$

But the variance differs:

$$VAR[y_i \mid \mathbf{x}_i] = \lambda_i\left(1+\alpha\cdot\lambda_i\right) = \exp(\mathbf{x}_i\boldsymbol{\beta})\left[1+\alpha\cdot\exp(\mathbf{x}_i\boldsymbol{\beta})\right] \qquad [5]$$

The parameter α in the equation [5] is commonly referred to as the over-dispersion parameter. In the negative binomial regression model, the probability of intersection i having y_i crashes per year (where y_i is a non-negative integer) for a given $\mathbf{x}$ is

$$P(y_i \mid \mathbf{x}_i) = \frac{\Gamma(\alpha^{-1}+y_i)}{\Gamma(\alpha^{-1})\cdot y_i!}\cdot\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_i}\right)^{\alpha^{-1}}\cdot\left(\frac{\lambda_i}{\alpha^{-1}+\lambda_i}\right)^{y_i}$$

where $\Gamma(\cdot)$ is a gamma function. This results in the likelihood function:

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{n}\frac{\Gamma(\alpha^{-1}+y_i)}{\Gamma(\alpha^{-1})\cdot y_i!}\cdot\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_i}\right)^{\alpha^{-1}}\cdot\left(\frac{\lambda_i}{\alpha^{-1}+\lambda_i}\right)^{y_i}$$

After taking logs, the log-likelihood function can be maximized with numerical methods, and an estimate of $\boldsymbol{\beta}$ is obtained.

In addition to the Poisson regression model (PRM) and the negative binomial regression model (NBRM), some researchers have proposed that zero-inflated models fit crash data better than NBRM in some cases. However, the zero-inflated model assumes an underlying dual-state process and may not be justified. Although statistical fit may be improved, the theoretical support for a dual-state process is lacking. Inherently, “safe” locations do not agree with this understanding of crash causation. Thus, PRM and NBRM are employed to find SPFs comprising AADT and the number of crashes.

Comparing models

The choice of using the PRM or NBRM is determined by assessing the significance of the over-dispersion parameter. Before explaining the test of over-dispersion parameter α, the following simple example would be helpful for better understanding of the concept of test. Figure 16 shows the essential difference between PRM and NBRM. It represents one of the results in estimating SPFs (specifically, total crashes occurring on all approaches vs. AADT). As mentioned in this section, the expected value of y is the same regardless of applied models (the black bold line indicates the expected value of y of the PRM and NBRM models). However, the variance of y is different depending on the chosen model. The dimmer black lines in both figures indicate the distribution of y for a given AADT— the equation [5]—for the fitted PRM and NBRM. This apparent difference between PRM and NBRM shown in the figure leads one to conclude visually that the over-dispersion parameter α is not zero.

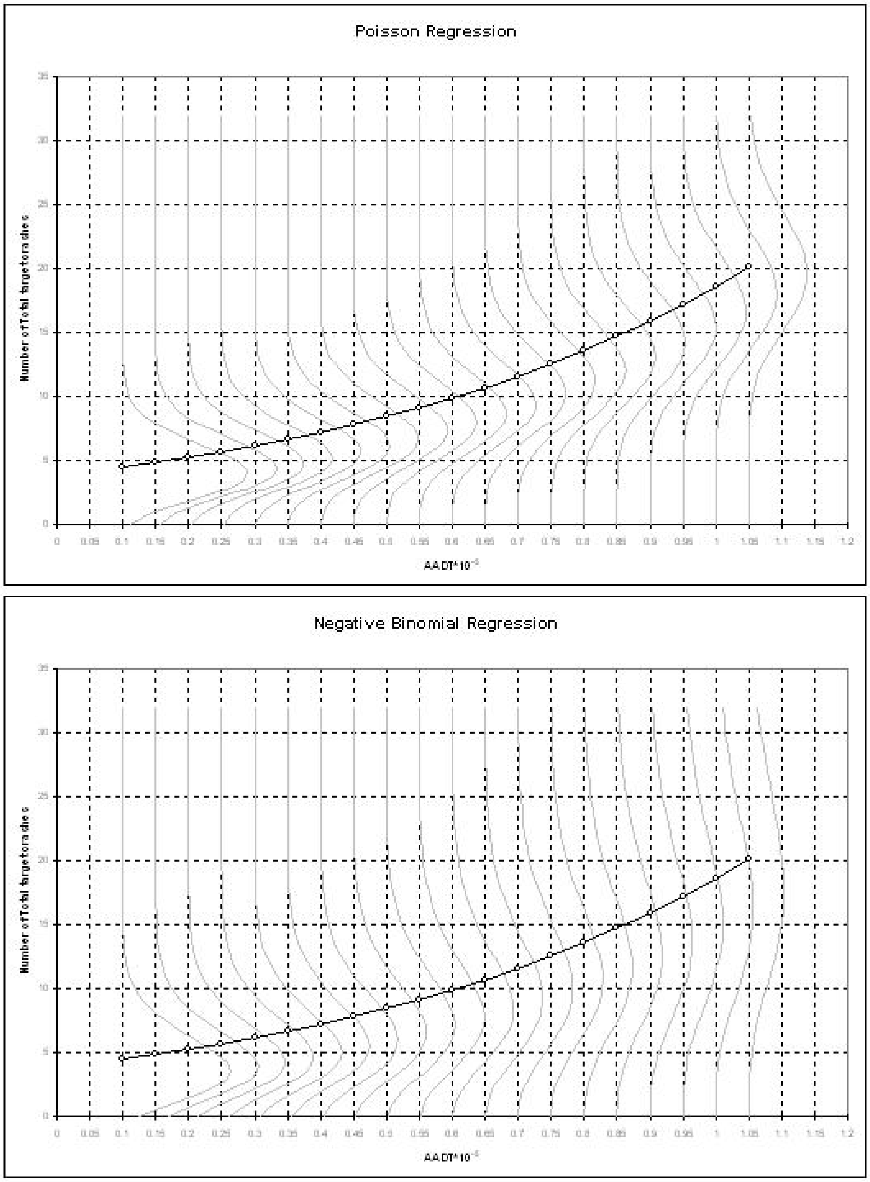

Figure 16: Modeled variance in PRM (top) and NBRM(bottom)

Statistically, the test for assessing the significance of the over-dispersion parameter is obtained by using the log-likelihood ratio test of α. Because NBRM reduces to PRM when α=0, PRM and NBRM can be compared by testing $H_0 : \alpha = 0$. The test statistic is given as $2(\ln L_{NBRM} - \ln L_{PRM})$, which is chi-squared distributed with degree of freedom 1. Thus, NBRM is preferred to the PRM when this log-likelihood ratio test statistics is greater than the critical value, indicating that chance alone would not produce a variance as large under the assumed Poisson dispersion.

Modeling Results by Crash Types: Target Approaches

To identify relationships between traffic flow and crashes, a matrix plot is shown in Figure 17. Although the relationships appear to be quite "noisy", crashes seem to reveal a slightly exponential increase as traffic flow increases for the crash types.

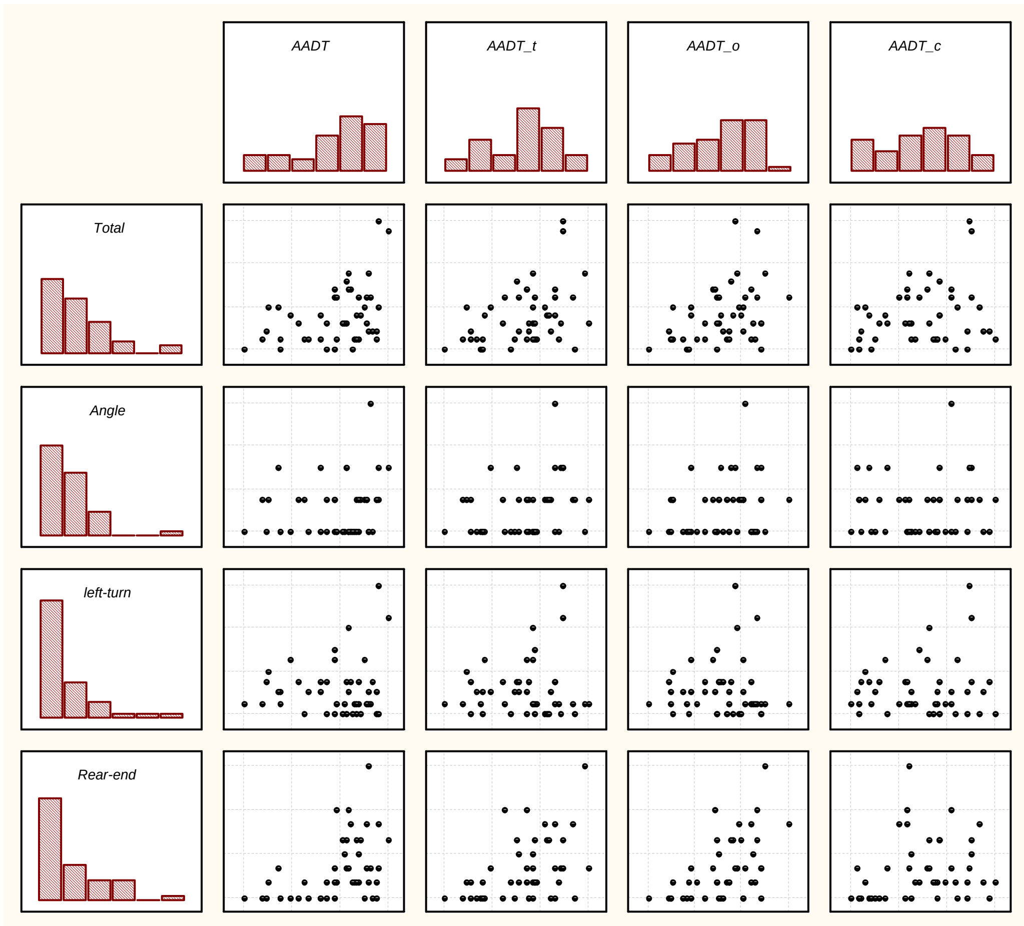

Figure 17: Matrix plot for the relationship between traffic flow and crashes

Table 42 shows the results of SPFs estimated using PRM and NBRM. In order to obtain SPFs, all possible independent variables ($AADT_t$, $AADT_o$, and $AADT_c$) are employed, and the best model for each crash type is determined by considering both the statistical results and the mechanism of each crash.

Table 42: The SPFs with traffic flow (target approaches)

Total (NBRM)	Total Crashes $=0.00116 \cdot AADT^{0.7486}$		
	Variable	**Estimated parameter**	**z-statistics**
	Constant	-6.75525	-2.35
	Ln(AADT)	0.748635	2.91
	Log likelihood ratio for Ho: $\boldsymbol{\beta}=0$ (and associated p-value)		8.28 (0.0040)
	Over-dispersion parameter: α		0.1767049
	Log likelihood ratio for Ho: α=0 (and associated p-value)		12.86 (0.000)
Angle (PRM)	Angle Crashes $=0.00011 \cdot AADT_t^{0.8814}$		
	Variable	**Estimated parameter**	**z-statistics**
	Constant	-9.12744	-1.69
	Ln($AADT_t$)	0.881438	1.64
	Log likelihood ratio for Ho: $\boldsymbol{\beta}=0$ (and associated p-value)		3.10 (0.0784)
	Over-dispersion parameter: α		-
	Log likelihood ratio for Ho: α=0 (and associated p-value)		-
Left-turn (NBRM)	Left-turn Crashes $=0.28191 \cdot AADT_c^{0.2109}$		
	Variable	**Estimated parameter**	**z-statistics**
	Constant	-1.26618	-0.45
	Ln($AADT_c$)	0.210852	0.77
	Log likelihood ratio for Ho: $\boldsymbol{\beta}=0$ (and associated p-value)		0.58 (0.4444)
	Over-dispersion parameter: α		0.6064404
	Log likelihood ratio for Ho: α=0 (and associated p-value)		25.04 (0.000)
Rear-end (NBRM)	Rear-end Crashes $=8.57E-09 \cdot AADT_t^{1.1939}$		
	Variable	**Estimated parameter**	**z-statistics**
	Constant	-18.5745	-3.49
	Ln($AADT_t$)	1.913928	3.62
	Log likelihood ratio for Ho: $\boldsymbol{\beta}=0$ (and associated p-value)		13.89 (0.0002)
	Over-dispersion parameter: α		0.4614633
	Log likelihood ratio for Ho: α=0 (and associated p-value)		9.84 (0.001)

NBRM is used for the SPF of total target crashes, left-turn crashes, and rear-end crashes, while PRM was employed for the SPF of angle crashes. In the NBRM for the SPF of angle crashes, the over-dispersion parameter α is not significant at the 0.05 level. Thus, the PRM is preferred to the NBRM. This result is expected because the mean of angle crashes (0.73) is similar to the variance (0.76), as shown in Table 40.

In addition, each SPF has a different independent variable (e.g. AADT, $AADT_t$, and $AADT_c$). For the total crashes, AADT is determined as an independent variable. It indicates total crashes would be associated with AADT rather than $AADT_t$, $AADT_o$, or $AADT_c$. On the other hand, $AADT_t$ is determined as an independent variable in the SPFs for angle and rear-end crashes. It is also reasonable because they are practically caused by the traffic flow on target approaches. For left-turn crashes, however, $AADT_c$ is determined as the best independent variable. This result is also defensible because left-turn crashes are the result of vehicle conflicts. The best fitting models are used for predicting the safety of a site given AADT. All estimated coefficients of independent variables and the test results of log-likelihood ratio for GOF except those for left-turn crashes are significant at the 0.05 level. Figures 18 through 21 show the predicted values and observed values as a function of AADT for these models.

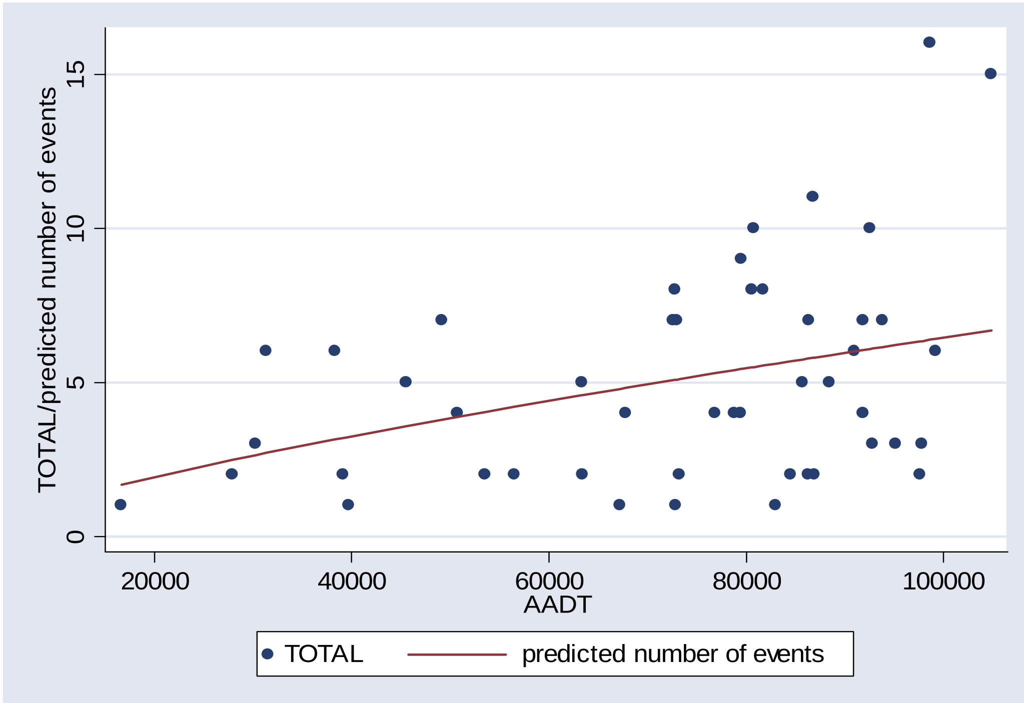

Figure 18: Relation of AADT and total target crashes (target approach)

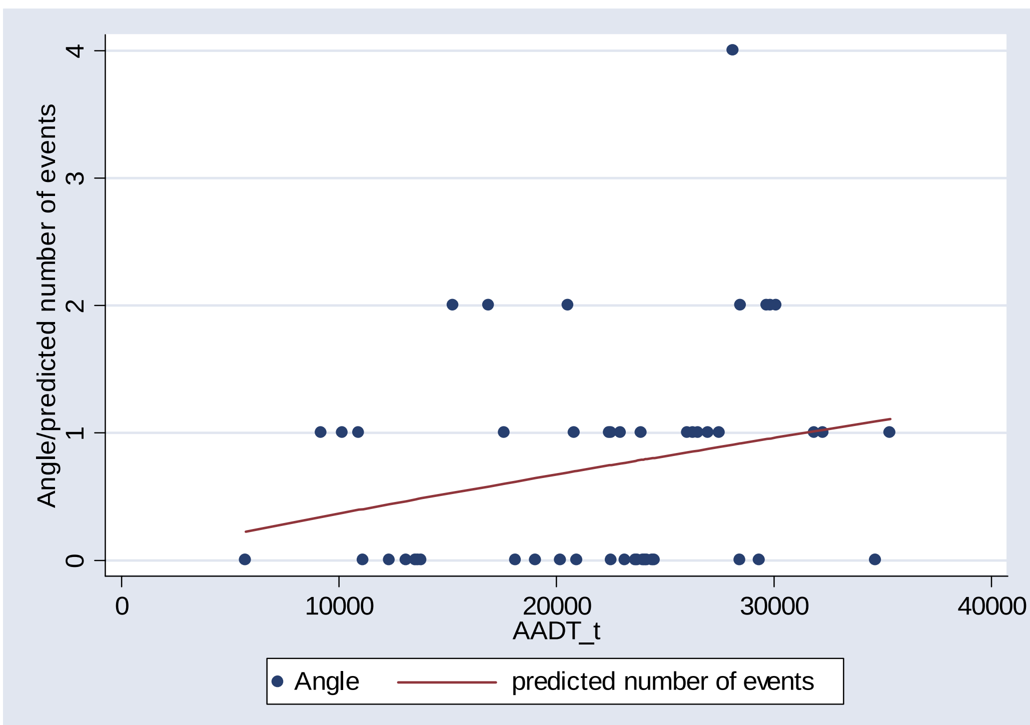

Figure 19: Relation of AADT_t and angle crashes (target approach)

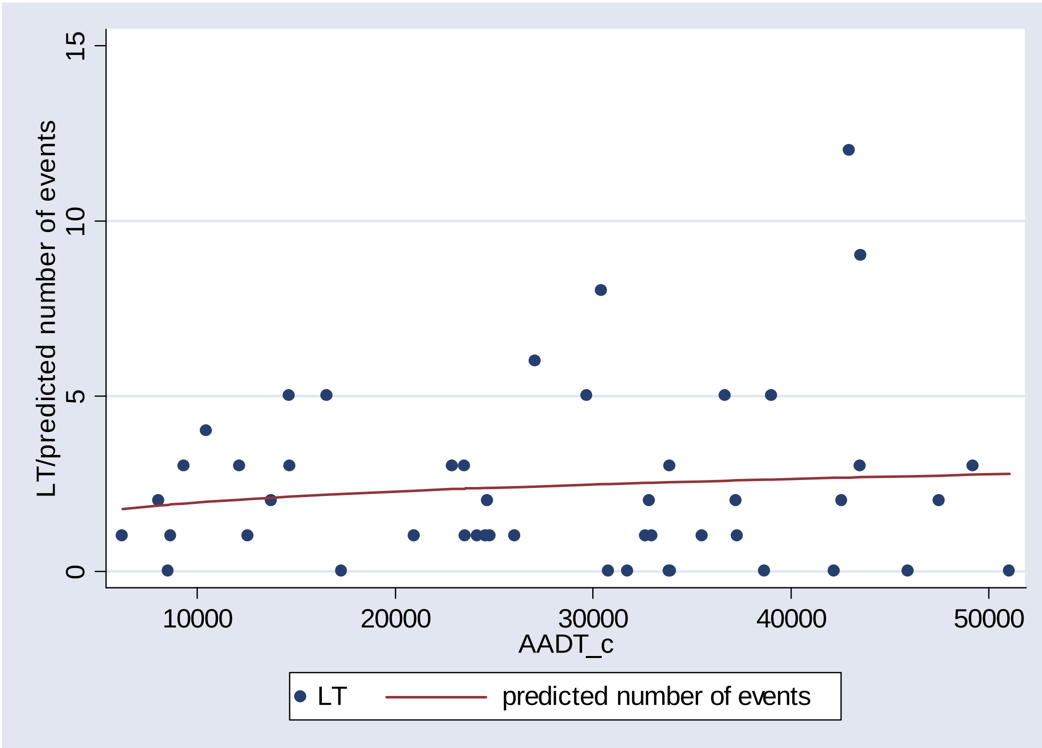

Figure 20: Relation of AADT_c and left-turn crashes (target approaches)

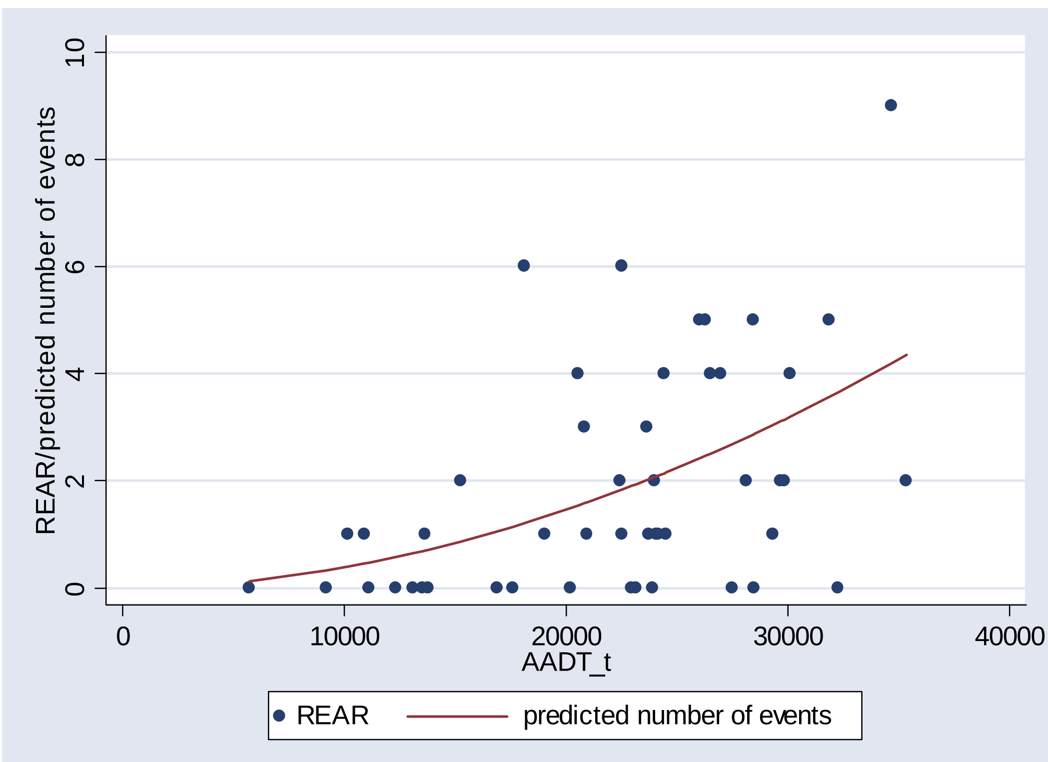

Figure 21: Relation of AADT_t and rear-end crashes (target approaches)

Modeling Results: All approaches

For investigating the relationship between crashes and traffic flow, a matrix plot is provided in Figure 22. As before, these relationships suggest curvilinear SPFs between AADT and safety.

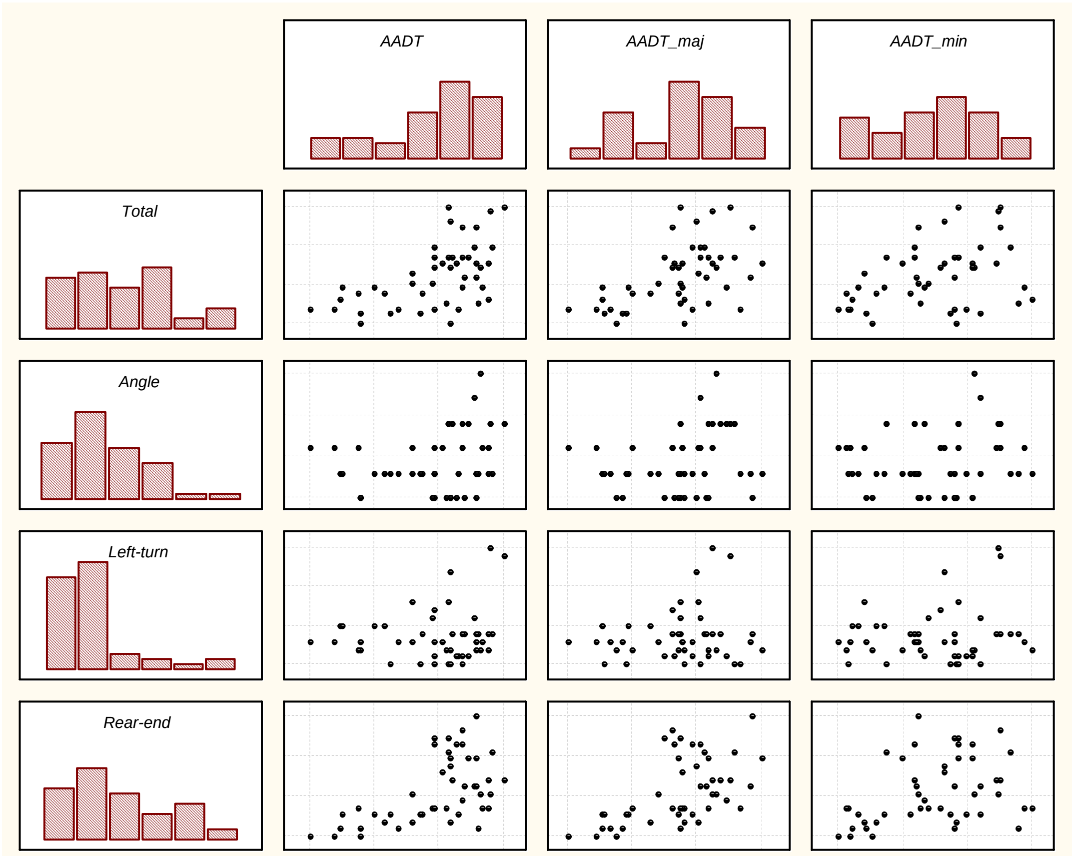

Figure 22: Matrix plot for the relationship between traffic flow and crashes (all approaches)

Table 43 shows the estimated SPFs using the NBRM and PRM. The NBRM is used for the SPF of total target crashes, left-turn crashes, and rear-end crashes, while the PRM is employed for the SPF for angle crashes. For the SPF for angle crashes, the PRM is preferred to the NBRM. This result is expected because the mean of angle crashes (1.47) is similar to the variance (1.51) shown in table 41.

In the case of all approaches, all SPFs have the same independent variable (e.g. AADT). All estimated coefficients of independent variables and the test results of log-likelihood ratio for GOF except those for angle and left-turn crashes are significant at the 0.05 significance level. For the left-turn and angle crashes, the insignificant results suggest that there is too much “noise” to “signal” in the data. Given that collective wisdom and significant prior research have shown that exposure is a primary predictor of crashes, it is assumed that these models still represent the “best” predictive models, hindered due to inadequate sample size.

Table 43: The SPFs with traffic flow (all approaches)

Model	Variable	Estimated parameter	z-statistics
Total (NBRM)	Total crashes = $0.00078 \cdot AADT^{0.8586}$		
	Variable	**Estimated parameter**	**z-statistics**
	Constant	-7.160402	-3.47
	Ln(AADT)	0.858578	4.66
	Log likelihood ratio for Ho: $\boldsymbol{\beta}$=0 (and associated p-value)		18.77 (0.0000)
	Over-dispersion parameter: α		0.1033756
	Log likelihood ratio for Ho: α=0 (and associated p-value)		18.57 (0.0000)
Angle (PRM)	Angle crashes = $0.08929 \cdot AADT^{0.2511}$		
	Variable	**Estimated parameter**	**z-statistics**
	Constant	-2.415845	-0.66
	Ln(AADT)	0.251085	0.77
	Log likelihood ratio for Ho: $\boldsymbol{\beta}$=0 (and associated p-value)		0.62 (0.4299)
	Over-dispersion parameter: α		-
	Log likelihood ratio for Ho: α=0 (and associated p-value)		-
Left-turn (NBRM)	Left-turn crashes =$0.33148 \cdot AADT^{0.2176}$		
	Variable	**Estimated parameter**	**z-statistics**
	Constant	-1.104181	-0.33
	Ln(AADT)	0.217626	0.73
	Log likelihood ratio for Ho: $\boldsymbol{\beta}$=0 (and associated p-value)		0.53 (0.4672)
	Over-dispersion parameter: α		0.4171307
	Log likelihood ratio for Ho: α=0 (and associated p-value)		29.63 (0.000)
Rear-end (NBRM)	Rear-end crashes = $0.000000002 \cdot AADT^{0.2176}$		
	Variable	**Estimated parameter**	**z-statistics**
	Constant	-19.70302	-5.19
	Ln(AADT)	1.918711	5.69
	Log likelihood ratio for Ho: $\boldsymbol{\beta}$=0 (and associated p-value)		31.74 (0.000)
	Over-dispersion parameter: α		0.1906724
	Log likelihood ratio for Ho: α=0 (and associated p-value)		20.38 (0.000)

Figures 23 through 26 show the predicted SPFs for the all approaches models. As was shown previously, the relationships are noisy but nonetheless capture the relationship between safety and exposure and support the claim that most SPFs are not straight line functions.

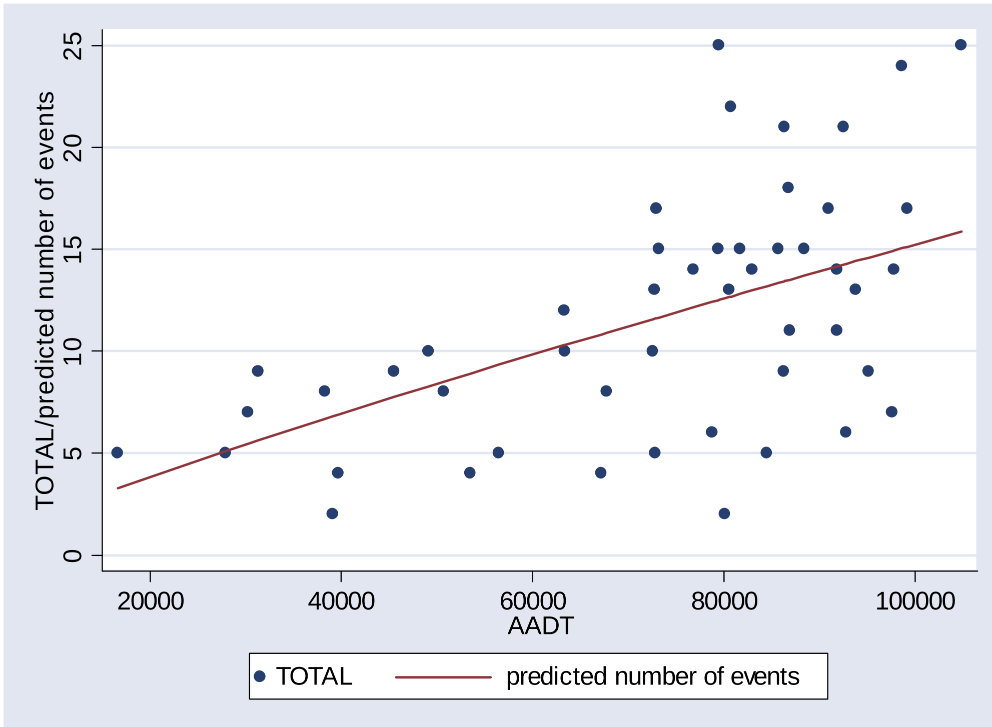

Figure 23: Relation of AADT and total crashes (all approaches)

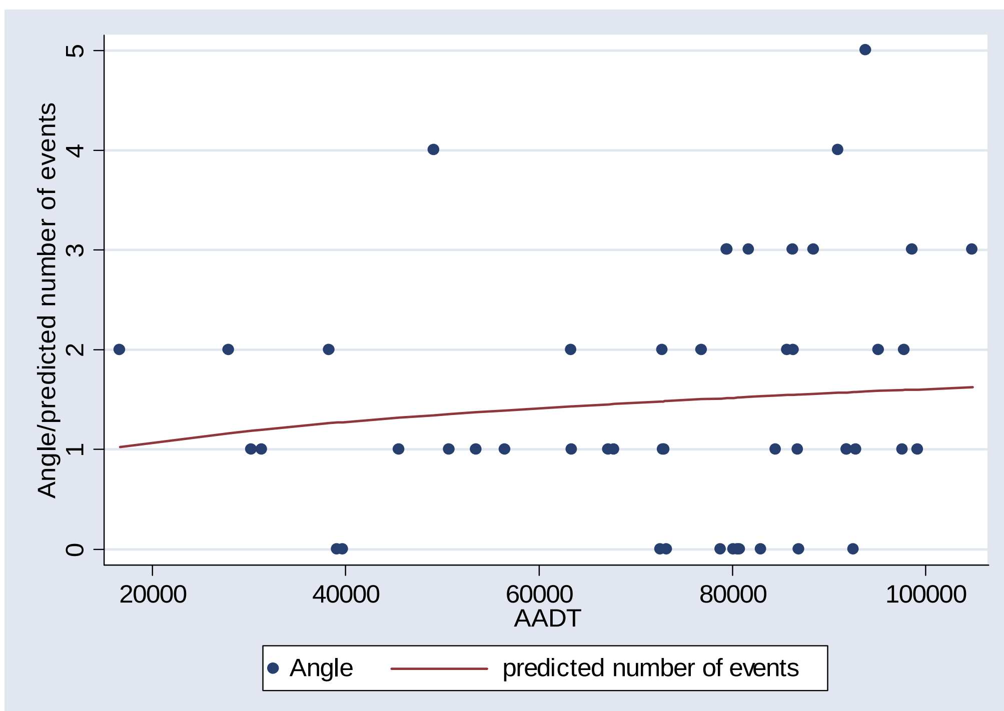

Figure 24: Relation of AADT and angle crashes (all approaches)

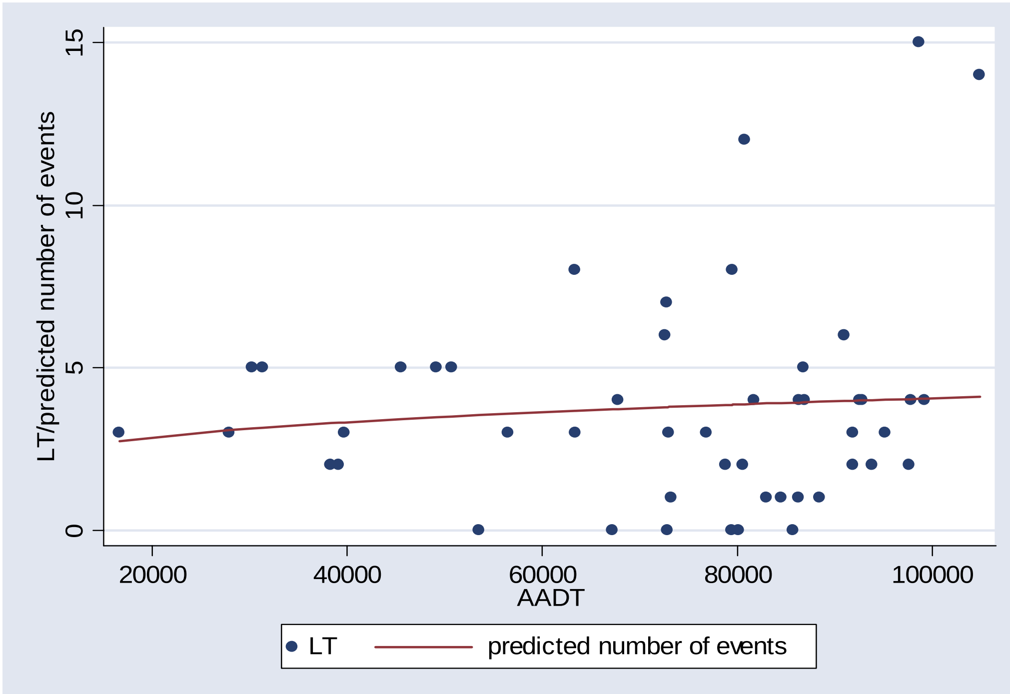

Figure 25: Relation of AADT and left-turn crashes (all approaches)

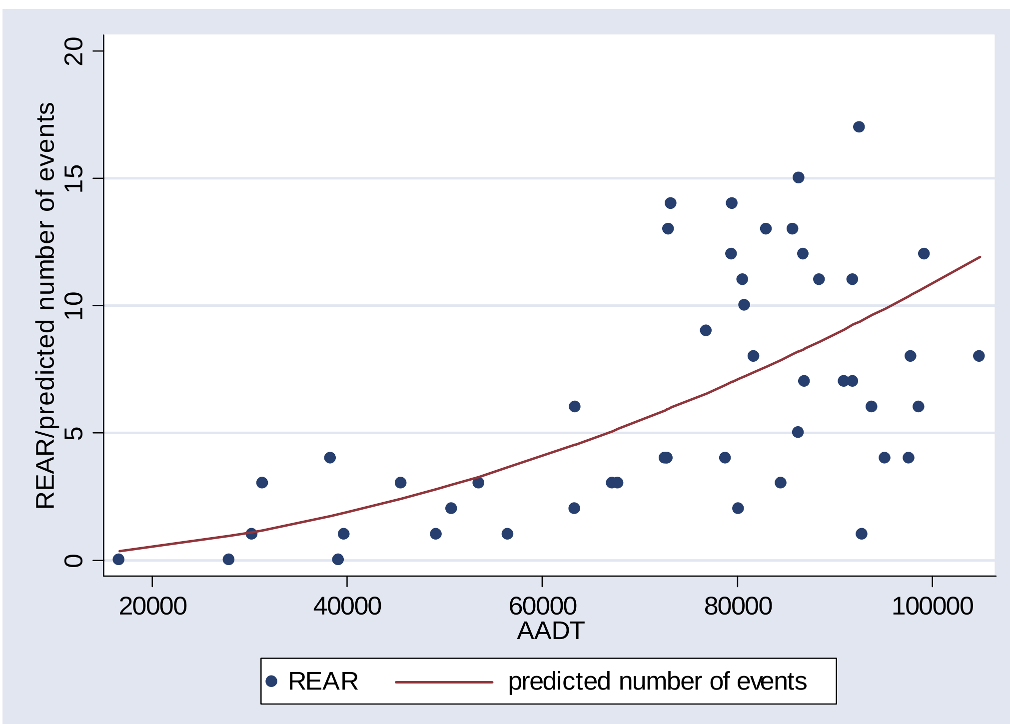

Figure 26: Relation of AADT and rear-end crashes (all approaches)

Prediction in before-after study with correction for traffic flow

When the change of traffic flow is considered, the 4-step procedure is corrected as described in the previous subsection. As mentioned previously, the estimate of π becomes

$$\hat{\pi} = \hat{r}_{tf} \cdot r_d \cdot K$$

Using the estimated SPFs (shown in Table 44), the estimate of the ratio of traffic flow, $\hat{r}_{tf}$, is be obtained. Recall that $\hat{r}_{tf}$ is

$$\hat{r}_{tf} = \frac{f\left(\hat{A}_{avg}\right)}{f\left(\hat{B}_{avg}\right)}$$

Table 44: Summary results of the estimated SPFs

	The estimated SPFs
All Approaches	Total crashes = $0.00078 \cdot AADT^{0.8586}$ Angle crashes = $0.08929 \cdot AADT^{0.2511}$ Left-turn crashes =$0.33148 \cdot AADT^{0.2176}$ Rear-end crashes = $0.000000002 \cdot AADT^{0.2176}$
Target Approaches	Total Crashes =$0.00116 \cdot AADT^{0.7486}$ Angle Crashes =$0.00011 \cdot AADT_t^{0.8814}$ Left-turn Crashes =$0.28191 \cdot AADT_c^{0.2109}$ Rear-end Crashes =$8.57E-09 \cdot AADT_t^{1.1939}$

Tables 45 and 46 indicate the average traffic flow for Scottsdale in the before and after periods. These average values are used as the estimates for A_{avg} and B_{avg}. With the results from Tables 44 to 46, the estimate of the ratio of traffic flow is calculated, and is shown in Table 47.

The estimated traffic flow correction factors ($\hat{r}_{tf}$) are less than 1 on average. This finding indicates that the expected number of crashes would be reduced if the red light cameras were not installed, on average. Although traffic flow generally increases over the time, Scottsdale had some significant traffic flow changes in the recent few years due to a freeway being constructed in the city, resulting in decreases in traffic flows in some of the after periods. In the 2 intersections (S8 and S12), however, a correction is not applied due to the lack of traffic flow data. Thus, the traffic flow correction is applied to 12 intersections out of the 14 intersections with the $\hat{r}_{tf}$ of two intersections being set to 1.

Table 45: The average AADT for Scottsdale in before and after periods (all approaches)

Intersection ID	Before		After	
	mean	n	mean	n
S1	49,164	1	47,600	3
S2	98,428	2	93,429	3
S3	63,344	1	67,280	3
S4	93,989	2	94,106	4
S5	86,648	2	68,034	2
S6	94,399	2	74,586	3
S7	86,770	1	91,266	5
S8	-	-	-	-
S9	83,174	6	80,767	1
S10	80,050	8	82,632	1
S11	84,111	8	-	-
S12	35,169	8	53,394	1
S13	55,605	2	45,091	1
S14	71,207	6	70,235	1
Sum	846,122	47	569,469	21

Table 46: The average traffic flow for Scottsdale in before-after periods (target approaches)

Intersection ID	Before			After		
	mean		n	mean		n
	AADTt	AADTc		AADTt	AADTc	
S1	16,895	14,660	1	17,449	12,281	3
S2	24,419	48,492	2	22,201	42,449	3
S3	28,482	12,133	1	29,995	12,745	1
S4	22,058	48,366	2	24,847	44,107	4
S5	28,924	27,300	2	25,303	18,780	2
S6	25,719	40,810	2	17,478	33,922	3
S7	26,035	36,694	1	28,024	38,150	5
S8	-	-	-	-	-	-
S9	25,177	33,799	5	20,821	39,019	1
S10	24,295	31,907	8	22,472	34,787	1
S11	28,243	24,801	8		-	-
S12	11,631	11,535	8	19,881	14,902	1
S13	23,765	8,304	2	18,812	7,895	1
S14	16,758	37,719	6	19,146	31,236	1
Sum	302,399	376,519	48	266,428	330,272	26

Table 47: Estimates of ratio of traffic flow, r_{tf}

Intersection ID	Total		Angle		Left-turn		Rear-end	
	All approaches	Target approaches	All approaches	Target approaches	All approaches	Target approaches	All approaches	Target approaches
S1	0.973	0.976	0.992	1.029	0.993	0.963	0.940	1.064
S2	0.956	0.962	0.987	0.920	0.989	0.972	0.905	0.833
S3	1.053	1.046	1.015	1.047	1.013	1.010	1.123	1.104
S4	1.001	1.001	1.000	1.111	1.000	0.981	1.002	1.256
S5	0.812	0.834	0.941	0.889	0.949	0.924	0.629	0.774
S6	0.817	0.838	0.943	0.711	0.950	0.962	0.636	0.477
S7	1.044	1.039	1.013	1.067	1.011	1.008	1.102	1.151
S8	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
S9	0.975	0.978	0.993	0.846	0.994	1.031	0.945	0.695
S10	1.028	1.024	1.008	0.934	1.007	1.018	1.063	0.861
S11	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
S12	1.431	1.367	1.111	1.604	1.095	1.055	2.228	2.790
S13	0.835	0.855	0.949	0.814	0.955	0.989	0.669	0.639
S14	0.988	0.990	0.997	1.125	0.997	0.961	0.974	1.290

By applying these traffic flow correction factors, the predicted values of π are obtained, and the results are shown in Table 48. Because of an average decrease in traffic flow in the after periods, the predicted values ($\hat{\pi}$) are slightly smaller than those obtained using the simple before-and-after study (see Table 37). If expected changes in safety that result from traffic flow changes are not accounted for, then the effects of the RLCs are overestimated on average.

Table 48: The number of crashes in the before-after study with correction of traffic flow

	Crash Types	K	$\hat{\pi}$	$\hat{\lambda}$
All approaches	Angle Crashes	207	160.2	113
	Left-turn Crashes	457	280.4	167
	Rear-end Crashes	676	361.6	590
	Total	1340	812.6	870
Target Approaches	Angle Crashes	91	73.5	62
	Left-turn Crashes	308	200.8	106
	Rear-end Crashes	199	108.7	184
	Total	598	387.2	352

In addition to predicting π, the variance of $\hat{\pi}$ plays a key role in obtaining the index of effectiveness and change in safety. Recall that it was

$$\hat{V}AR[\hat{\pi}] \cong r_d^{\,2}\left\{\hat{r}_{tf}^{\,2}\cdot\hat{V}AR[K] + K^2\cdot\hat{V}AR[\hat{r}_{tf}]\right\},$$

where the variance of $\hat{r}_{tf}$ is estimated as follows:

$$\hat{V}AR[\hat{r}_{tf}] \cong \hat{r}_{tf}^{\,2} \cdot \left(\frac{\hat{V}AR\left[f\left(\hat{A}_{avg} \right) \right]}{f^2\left(\hat{A}_{avg} \right)} + \frac{\hat{V}AR\left[f\left(\hat{B}_{avg} \right) \right]}{f^2\left(\hat{B}_{avg} \right)} \right).$$

Again, the variance of the expected number of accident in both periods using SPFs is estimated by:

$$\begin{aligned} \hat{V}AR\left[f\left(\hat{A}_{avg} \right) \right] &\cong \hat{V}AR[\hat{A}_{avg}] \cdot \left(\frac{\partial f\left(\hat{A}_{avg} \right)}{\partial \hat{A}_{avg}} \right)^2 \\ \hat{V}AR\left[f\left(\hat{B}_{avg} \right) \right] &\cong \hat{V}AR[\hat{B}_{avg}] \cdot \left(\frac{\partial f\left(\hat{B}_{avg} \right)}{\partial \hat{B}_{avg}} \right)^2 \end{aligned}.$$

The only remaining unknown quantity is the variance of the expected number of accidents in the before and after periods. Normally these quantities are obtained using detector data from the roadways, where traffic volumes are collected during specified periods. Then, by aggregating the detector data, the average daily traffic and the variance of average daily traffic are calculated, and the coefficient of variation (CV) is subsequently obtained.

In this study, however, the details of traffic volume data collection efforts are not known. An alternative way to estimate the variance of expected number of accidents is to refer to previous research results, however, previous research does not include all combinations of roadway classifications, duration of counts, etc. Hauer provides yet another method for estimating the coefficient of variation (Hauer, 1997) of crash counts, where

$$CV = 1 + \frac{7.7}{n} + \frac{1650}{AADT^{0.82}}$$

where n is the number of count days. For example, the CV of AADT for the S2 intersection is

$$CV = 1 + \frac{7.7}{2} + \frac{1650}{98,428^{0.82}} = 4.98\%$$

Table 49 shows the estimated coefficients of variation. The variance is then calculated using the CV.

Table 49: The estimated coefficients of variation for Scottsdale RLC intersections

Intersection ID	AADT		AADTt		AADTc	
	Before	After	Before	After	Before	After
S1	8.93	3.81	9.26	4.12	9.33	4.30
S2	4.98	3.71	5.27	4.02	5.09	3.83
S3	8.89	3.75	9.07	9.05	9.44	9.41
S4	4.99	3.06	5.30	3.34	5.09	3.18
S5	5.00	5.03	5.21	5.25	5.23	5.37
S6	4.99	3.73	5.25	4.11	5.12	3.88
S7	8.85	2.68	9.10	2.91	9.00	2.83
S8	-	-	-	-	-	-
S9	2.44	8.86	2.95	9.17	2.86	8.98
S10	2.12	8.85	2.38	9.15	2.30	9.01
S11	2.11	-	2.33	-	2.37	-
S12	2.27	8.92	2.73	9.19	2.73	9.32
S13	5.06	8.95	5.28	9.22	5.86	9.75
S14	2.46	8.88	2.85	9.21	2.57	9.04

With these quantities, the estimate of variances of $\hat{\pi}$ and standard deviations are obtained. The estimated standard deviations are shown in Table 50. As mentioned previously, the correction for two intersections shaded in the table could not be calculated due to the lack of traffic flow data.

Table 50: The estimated standard deviation of $\hat{\pi}$ for Scottsdale RLC intersections

ID	All approaches				Target approaches			
	Total	Angle	Left-turn	Rear-end	Total	Angle	Left-turn	Rear-end
S1	12.38	5.05	7.75	5.88	9.16	4.19	7.08	2.04
S2	10.19	3.42	4.10	9.39	5.45	2.10	2.21	4.13
S3	6.49	1.89	3.23	5.50	4.25	1.55	2.56	2.84
S4	12.00	3.93	7.55	8.26	7.39	2.53	5.61	4.91
S5	8.93	4.28	2.49	7.12	5.28	2.89	1.21	4.48
S6	10.45	5.53	6.11	5.92	6.21	2.84	4.72	1.75
S7	16.24	4.61	7.89	14.52	11.09	3.50	7.75	6.51
S8	10.15	7.17	5.71	4.34	8.18	5.07	5.56	3.21
S9	4.78	1.23	1.32	5.97	1.92	0.53	1.10	1.18
S10	5.12	1.06	2.61	3.96	3.09	0.69	2.20	1.30
S11	3.49	1.17	1.57	2.89	2.11	0.52	1.08	1.73
S12	1.99	0.51	1.04	1.25	1.09	0.37	0.74	0.37
S13	1.43	0.48	0.65	1.13	0.89	0.31	0.64	0.43
S14	1.63	0.37	0.68	1.72	0.84	0.30	0.45	0.95

Now, it is possible to quantify the effect of the RLCs accounting for changes in traffic flow. Even though the correction for two intersections was not applied, a comparison of the results with those obtained from the simple before-and-after study is meaningful. In the next section, the estimated impacts of RLCs are summarized when traffic flow is considered.

Analysis Results: Changes in safety and index of effectiveness

In the simple before-and-after study 4-step procedure, steps 3 and 4 are produce estimates of the change in safety and index of effectiveness respectively. In addition, the variances of these parameters are estimated. Table 51 shows these results after adjustments for traffic flows are made.

Table 51: Results of before-after study with correction of traffic flow

Jurisdiction	Crash Types	Change in Safety		Index of Effectiveness	
		$\hat{\delta}$	$S[\hat{\delta}]$	$\hat{\theta}$	$S[\hat{\theta}]$
All Approaches	Angle Crashes	47.24	17.19	0.70	0.09
	Left-turn Crashes	113.45	21.51	0.59	0.06
	Rear-end Crashes	-228.37	34.53	1.62	0.13
	All Crashes	-57.39	44.03	1.07	0.06
Target Approaches	Angle Crashes	11.46	12.18	0.83	0.15
	Left-turn Crashes	94.84	17.95	0.52	0.06
	Rear-end Crashes	-75.31	17.90	1.67	0.22
	All Crashes	35.24	28.55	0.91	0.07

When compared with the results of simple before-and-after study, the effects of red light cameras on safety are slightly reduced due to the correction of traffic flow in both the all approaches and target approaches analyses. These results suggest that effects estimated using the simple before-and-after study are overestimated. Figure 27 shows the 95% confidence intervals for indexes of effectiveness in Scottsdale.

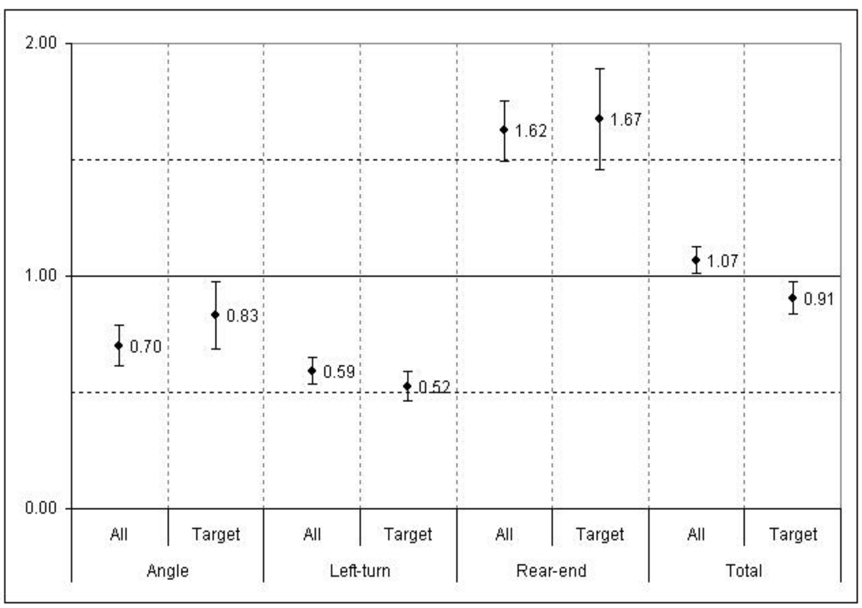

Figure 27: 95% CIs for indexes of effectiveness (correction for traffic volumes)

Analysis Method 3: Before-After Study with Comparison Group

In this analysis, the impact of red light cameras on safety is evaluated using a comparison group approach. Explicitly, this analysis is different from the previous before-and-after study (with traffic flow correction) in that it attempts to consider unrecognized factors, which cannot be modeled easily. In order to consider the effects of unrecognized factors in the analysis, generally a comparison group method is employed. The key assumption for comparison group methodologies is that the ratio of before to after target crashes is the same at treated and comparison sites (in the absence of the treatment). This suggests that unobserved changes in safety, such as driving population, traffic, weather, etc., affect comparison sites in the same way as treated sites. The comparison group analysis is applied to Phoenix data due to the lack of data for comparison sites in Scottsdale.

Correction in 4-step for Comparison Group Method

To provide a better understanding of the analysis methodology of the comparison group method, hypothetical data for target crashes and comparison crashes are shown in Figure 28. In this example, the duration of before and after data is 5 years, and k_i and l_i represent the observed number of target crashes in the before and after periods respectively. Also, m_i and n_i represent the observed number of comparison crashes in the before and after periods respectively.

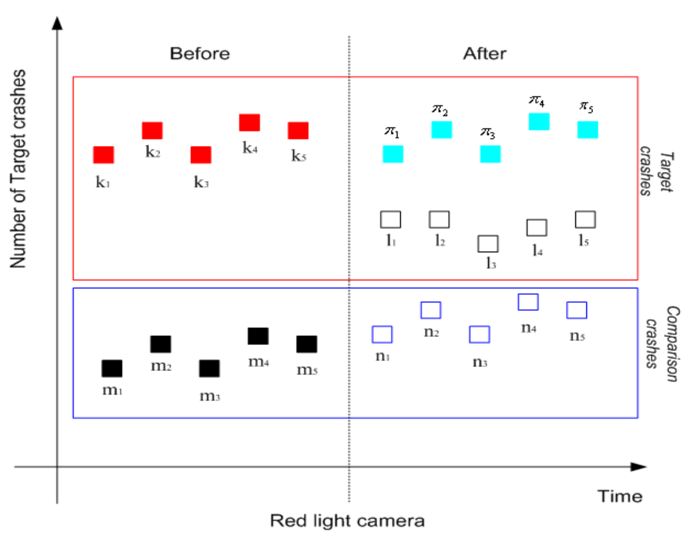

Figure 28: Before-after study with comparison group correction

Again, K, L, M, and N represent the sums of the observed number of crashes during each 5 year period. Table 52 shows the observed counts of crashes and the expected crash counts (Greek letters). These quantities are used to illustrate the analysis approach.

Table 52: The observed number of crashes and expected values

	Target crashes at treated Sites	Target crashes at comparison sites
Before	K (κ)	M (μ)
After	L (λ)	N (ν)

Step 1: Estimate λ and predict π

The first step is to estimate λ and predict π. Again, the estimate of λ is equal to the sum of the observed number of crashes in the after period.

$$\hat{\lambda} = \sum_{i=1}^{5} l_i = L$$

In order to predict π, the underlying assumption for the comparison method is employed. As mentioned, the key assumption for the comparison method is that the ratio of the expected number of target crashes in both periods is the same for treated and comparison sites. That is, it requires

$$\left(r_T = \frac{\pi}{\kappa}\right) = \left(r_C = \frac{\nu}{\mu}\right)$$

where,

r_T = the ratio of the predicted number to observed before target crashes at the treated sites,

r_C = the ratio of ratio of after to before target crashes at comparison sites.

Because r_T is equal to r_C under the assumption of the comparison method, π is obtained using $\pi = r_C \cdot \kappa$,

where 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. Thus, the estimate of r_C is

$$\hat{r}_T = \hat{r}_C = \frac{\left(\frac{N}{M}\right)}{\left(1 + \frac{1}{M}\right)} \cong \frac{N}{M}$$

Therefore, an estimate of π is

$$\hat{\pi} = \hat{r}_T \cdot \hat{\kappa} = \hat{r}_C \cdot \hat{\kappa} = \frac{\left(\frac{N}{M}\right)}{\left(1 + \frac{1}{M}\right)} \cdot K$$

Step 2: Estimate $\hat{\sigma}^2[\hat{\lambda}]$ and $\hat{\sigma}^2[\hat{\pi}]$

Due to the property of the Poisson distribution, the variance is equal to the mean. Thus, the estimate of variance for $\hat{\lambda}$ is $\widehat{VAR}[\hat{\lambda}] = L$, and the estimate of variance for $\hat{\pi}$ is estimated using the delta method to obtain

$$
\begin{aligned}
\widehat{VAR}[\hat{\pi}] &\cong \hat{r}_T{}^2 \cdot \widehat{VAR}[K] + K^2 \cdot \widehat{VAR}[\hat{r}_T] \\
&= \hat{r}_T{}^2 \cdot K^2 \cdot \left[\frac{1}{K} + \frac{\widehat{VAR}[\hat{r}_T]}{\hat{r}_T{}^2} \right] \\
&= \hat{\pi}^2 \cdot \left[\frac{1}{K} + \frac{\widehat{VAR}[\hat{r}_T]}{\hat{r}_T{}^2} \right]
\end{aligned}
$$

However, the variance of $\hat{r}_T$ is not known, but can also be obtained using the delta method. For convenience, the ratio of r_T and r_C is defined as the odds ratio: $\omega = r_C / r_T$, then, r_T is expanded as follows:

$$
\begin{aligned}
r_T &= \frac{r_C}{\omega} = \frac{(\nu/\mu)}{\omega} \\
\hat{r}_T &= \frac{\left(N/M \right)}{\hat{\omega}}
\end{aligned}
$$

Thus, the variance of $\hat{r}_T$ is

$$
\begin{aligned}
\widehat{VAR}[\hat{r}_C] &\cong VAR[\nu] \cdot \left(\frac{\partial r_C}{\partial \nu} \right)^2 + VAR[\mu] \cdot \left(\frac{\partial r_C}{\partial \mu} \right)^2 + VAR[\omega] \cdot \left(\frac{\partial r_C}{\partial \omega} \right)^2 \\
&= \hat{r}_C{}^2 \cdot \left(\frac{1}{M} + \frac{1}{N} + \frac{VAR[\omega]}{E^2[\omega]} \right)
\end{aligned}
.
$$

As a result, the estimate of variance for $\hat{\pi}$ is expressed as:

$$
\widehat{VAR}[\hat{\pi}] \cong \hat{\pi}^2 \cdot \left[\frac{1}{K} + \left(\frac{1}{M} + \frac{1}{N} + \frac{VAR[\omega]}{E^2[\omega]} \right) \right] .
$$

With these corrections to the 4 step process, the remaining steps (step 3 and step 4) continue as before. Table 53 shows the corrected 4-step used in the comparison method.

Table 53: Corrected 4-step for before-after study with comparison group

Step	Goals	Formulas for before-and-after study with comparison crashes
Step 1	Estimate λ and predict π	$\hat{\lambda} = L$ $\hat{\pi} = \hat{r}_T \cdot \hat{\kappa} = \hat{r}_C \cdot \hat{\kappa} = \dfrac{\left(\dfrac{N}{M}\right)}{\left(1 + \dfrac{1}{M}\right)} \cdot K$
Step 2	Estimate $\hat{\sigma}^2[\hat{\lambda}]$ and $\hat{\sigma}^2[\hat{\pi}]$	$\widehat{VAR}[\hat{\lambda}] = L$ $\widehat{VAR}[\hat{\pi}] \cong \hat{\pi}^2 \cdot \left[\dfrac{1}{K} + \dfrac{\widehat{VAR}[\hat{r}_C]}{\hat{r}_C{}^2}\right] or$ $= \hat{\pi}^2 \cdot \left[\dfrac{1}{K} + \left(\dfrac{1}{M} + \dfrac{1}{N} + \dfrac{VAR[\omega]}{E^2[\omega]}\right)\right]$ $\because \widehat{VAR}[\hat{r}_C] \cong \hat{r}_C{}^2 \cdot \left(\dfrac{1}{M} + \dfrac{1}{N} + \dfrac{VAR[\omega]}{E^2[\omega]}\right)$
Step 3	Estimate δ and θ	$\hat{\delta} = \hat{\pi} - \hat{\lambda}$ $\hat{\theta} \cong \dfrac{\left(\dfrac{\hat{\lambda}}{\hat{\pi}}\right)}{\left(1 + \dfrac{\widehat{VAR}[\hat{\pi}]}{\hat{\pi}^2}\right)}$
Step 4	Estimate $\hat{\sigma}^2[\hat{\delta}]$ and $\hat{\sigma}^2[\hat{\theta}]$	$\hat{\sigma}^2[\hat{\delta}] = \hat{\pi} + \hat{\lambda}$ $\hat{\sigma}^2[\hat{\theta}] \cong \dfrac{\hat{\theta}^2 \cdot \left[\dfrac{\widehat{VAR}(\hat{\lambda})}{\hat{\lambda}^2} + \dfrac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^2}\right]}{\left[1 + \dfrac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^2}\right]^2}$

Prediction with Comparison Crashes

In the comparison method, the estimate of π is defined as

$$\hat{\pi} = r_d \cdot \hat{r}_T \cdot \hat{\kappa} = r_d \cdot \hat{r}_C \cdot \hat{\kappa} = r_d \cdot \frac{\left(\frac{N}{M}\right)}{\left(1+\frac{1}{M}\right)} \cdot K \qquad [6]$$

Equation [6] is slightly different from step 1 shown in Table 53 because of the ratio of durations (r_d). In Equation [6], the ratio of crashes in both periods of the comparison groups plays a role in obtaining the estimate of π. In order to obtain the ratio, the 13 comparison sites are considered. The duration of data and the number of RLC crashes are:

- Duration of data: October 1, 1998 to September 9, 2003 (5 years)
- Number of RLC crashes: 1,884 over 5 years

The comparison sites should have similar characteristics except for treatment because of the key assumption of the comparison group method. The comparison sites were provided by the City of Phoenix and were selected because of their high crashes frequencies as well as other similar characteristics to the treatment sites. In order to compare the crashes of treated sites (i.e., RLC intersections) with the comparison sites, the same criteria for the selection of target crashes are applied to all comparison sites. Table 54 shows the summary crash statistics for the comparison sites (with target crashes extracted).

Table 54: Summary of crashes history of comparison sites

Intersection Name	Angle	Left Turn	Rear End	Total
CAMELBACK RD & 19TH AV	20	100	60	180
CAMELBACK RD & 27TH AV	24	65	36	125
19TH AV & DUNLAP AV	30	80	40	150
INDIAN SCHOOL RD & 27TH AV	22	84	34	140
59TH AV & INDIAN SCHOOL RD	23	63	27	113
INDIAN SCHOOL RD & 67TH AV	24	94	40	158
MCDOWELL RD & 7TH ST	42	58	38	138
MCDOWELL RD & 16TH ST	20	61	30	111
43RD AV & MCDOWELL RD	23	74	33	130
19TH AV & NORTHERN AV	26	156	68	250
16TH ST & THOMAS RD	14	69	38	121
THOMAS RD & 51ST AV	22	89	28	139
59TH AV & THOMAS RD	15	82	31	128
Mean	*23.46*	*82.69*	*38.69*	*144.85*
Standard Deviation	*6.97*	*25.65*	*12.13*	*36.77*

Using data from these comparison intersections, the ratio ({N/M}/{1+1/M}) can be calculated for each. Table 55 shows these comparison ratios. They are slightly greater than 1, which means the target crashes in the comparison group have increased in the after period, for all crash types, although the increases are relatively small.

Table 55: The estimates of comparison ratios

Intersection Name	Angle	Left Turn	Rear End	Total
P1	1.162	1.086	1.086	1.045
P2	1.162	1.086	1.086	1.045
P3	1.090	1.066	1.093	1.045
P4	1.090	1.066	1.093	1.045
P5	1.034	1.046	1.045	1.028
P6	1.034	1.046	1.045	1.028
P7	1.008	1.078	1.024	1.049
P8	1.008	1.078	1.024	1.049
P9	1.008	1.078	1.024	1.049
P10	1.008	1.078	1.024	1.049

With these comparison ratios, the predicted values of π are estimated. Table 56 displays the prediction results. Because of the increasing trend in crashes revealed by the comparison group, the predicted values ($\hat{\pi}$) are slightly greater than those in the simple before-and-after study (see Table 37). That is, after considering the increasing trend in crashes at comparison sites, the predicted number of crashes in the after period at treated sites is higher than predicted by the naïve or simple before-and-after study.

Table 56: The number of crashes in the before-after study with correction ratio

	Crash Types	K	$\hat{\pi}$	$\hat{\lambda}$
All approaches	Angle Crashes	97.0	65.2	56.0
	Left-turn Crashes	335.0	228.1	226.0
	Rear-end Crashes	201.0	134.7	162.0
	Total	633.0	419.2	444.0
Target Approach	Angle Crashes	50.0	34.5	20.0
	Left-turn Crashes	197.0	135.0	122.0
	Rear-end Crashes	81.0	55.0	83.0
	Total	328.0	218.9	225.0

In addition, the estimates of variance of $\hat{\pi}$ are required. Under the assumption that the ratios of after to before target crashes are the same in the treated and comparison sites, the expected value and variance of odds ratio (ω) should be approximately equal to 1. Thus, the equation for the variance of $\hat{\pi}$ is reduced to:

$$\hat{V}AR[\hat{\pi}] \cong r_d^{\,2} \cdot \hat{\pi}^2 \cdot \left[\frac{1}{K} + \frac{1}{M} + \frac{1}{N}\right] \quad . \qquad [7]$$

The estimates of variance of $\hat{\pi}$ are easily calculated using the equation [7]. Again, with the predicted value and estimates of variance, the effects are quantified, and the results are described in the next part.

Analysis Results: Changes in safety and indexes of effectiveness

In the 4-step procedure for the before-and-after study, steps 3 and 4 are performed to estimate the change in safety and index of effectiveness. In addition, the variances for these parameters are estimated. Table 57 shows the results for the before-and-after study with comparison groups.

Table 57: Results of before-after study with comparison group corrections

Jurisdiction	Crash Types	Change in safety		Index of effectiveness	
		$\hat{\delta}$	$S[\hat{\delta}]$	$\hat{\theta}$	$S[\hat{\theta}]$
All Approaches	Angle Crashes	9.17	7.79	0.86	0.12
	Left-turn Crashes	2.15	15.19	0.99	0.07
	Rear-end Crashes	-27.27	12.92	1.20	0.10
	All Crashes	-24.79	21.18	1.06	0.05
Target Approaches	Angle Crashes	14.46	4.89	0.58	0.13
	Left-turn Crashes	13.01	11.24	0.90	0.08
	Rear-end Crashes	-27.97	9.35	1.51	0.17
	All Crashes	-6.05	15.15	1.03	0.07

When compared with the results of the simple before-and-after study, the effects of red light cameras on safety slightly improve due to the correction of unrecognized factors in the comparison ratios. Figure 29 shows the 95% confidence intervals for indexes of effectiveness.

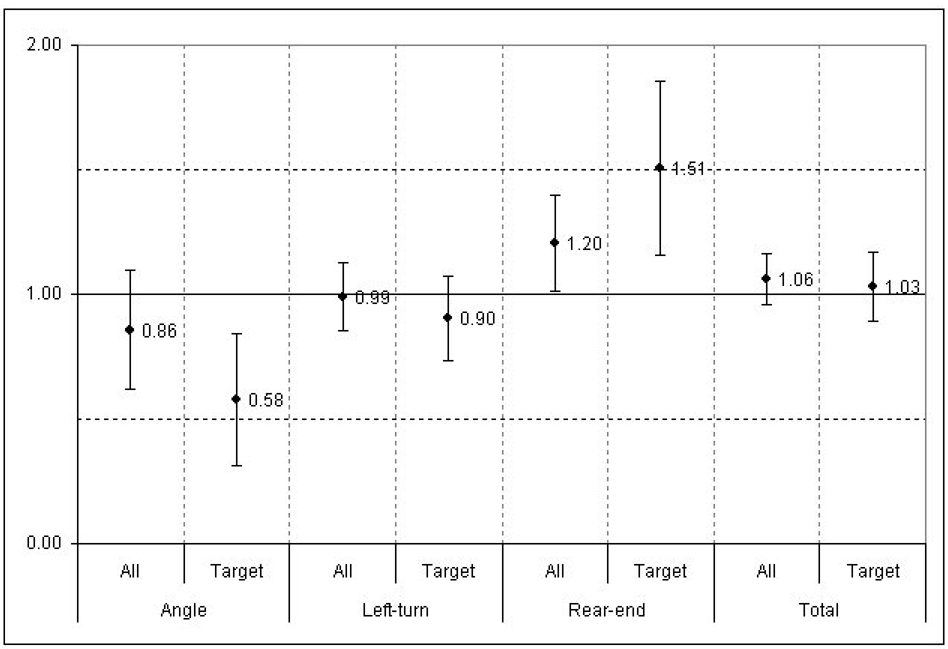

Figure 29: 95% CIs for indexes of effectiveness (comparison group method)

Analysis Method 4: Empirical Bayes' Before-After Study

The naïve or simple before-and-after study assumed no changes from the before to after periods—often an unrealistic assumption. The primary factor affecting crashes, traffic volumes, were accounted for in the second analysis (for the City of Scottsdale). All factors, observed and unobserved, are accounted for in the third analysis (for the City of Phoenix). None of these analysis approaches have considered a possible regression to the mean effect, caused by the selection of sites for treatment (RLCs) because their crash rates are high. In this section the regression-to-the-mean phenomenon is described (i.e., what is the regression-to-the-mean? Why is this common phenomenon problematic?), and the empirical Bayesian method—designed to correct for regression to the mean—is described and applied in the before-and-after study. Due to the lack of a complete dataset, however, it is applied only to the city of Scottsdale data.

Overview of Regression-to-mean bias and Empirical Bayesian method

In previous approaches, the observed crash count in the before period (K) plays a key role in estimating "π" with the correction factors such as the duration, the change in traffic flow, or the number of crashes in the comparison group. However, it is necessary to consider the expected value of K in safety studies due to possible regression-to-mean bias.

In an observational study, there is likely to be a link between the decision to treat an entity and its accident history. This link causes so called regression-to-mean bias (hereafter RTM bias). If an entity is treated because its "before" accident count (K) was abnormally high or unusually low, then the same K cannot possibly be a good estimate of π (Hauer, 1997).

In order to investigate the RTM phenomenon, the crash data at 218 non-RLC intersections in Scottsdale from 1995 to 1996 are summarized in Table 58. In this table, the "K_{95}" and "# of intersections" indicate the categories and frequencies (the count of crashes) respectively in 1995. However, "K_{96}" is the average number of crashes that occurred at the same intersections during 1996.

Table 58: Number of crashes at 218 intersections in Scottsdale during 1995 to 1996

# of intersections (N_{95})	K_{95}	K_{96}	# of intersections (N_{95})	K_{95}	K_{96}
38	0	0.47	6	12	8.67
9	1	4.56	5	13	11.40
16	2	3.75	7	14	18.71
16	3	3.88	4	15	12.50
14	4	4.14	5	16	11.60
13	5	5.54	3	17	16.67
5	6	6.20	2	18	19.50
12	7	8.17	3	19	18.67
3	8	11.33	4	20	15.50
6	9	6.83	…	…	…
8	10	14.00	…	…	…
4	11	9.75	1	62	42.00

Suppose that there were no treatments and no changes in recognized and unrecognized factors affecting safety from 1995 to 1996. The average crash frequency in 1995 (10.2) is similar to that in 1996 (10.5), and so the assumption is reasonable. Then, it is expected that there is little difference between K_{95} and K_{96}. However, the summary in Table 58 shows that there are indeed some differences. Moreover, the differences possess a specific trend. Figure 30 shows the changes in crash frequency, which is called RTM phenomenon. If the crash frequency in 1995 at a particular site was less than the average crash frequency in 1995 (10.2), the average crash frequency in 1996 on average increased. On the contrary, if the crash frequency in 1995 was greater than the average crash frequency (10.2), the average crash frequency in 1996 decreased on average. Due to sampling variability, there are three points (9, 14, and 18 crashes in 1995) that did not follow this trend. However, the average number of crashes in 1996 regressed to the mean (10.2) overall for the majority of sites. These data and the figure illustrate the RTM phenomenon.

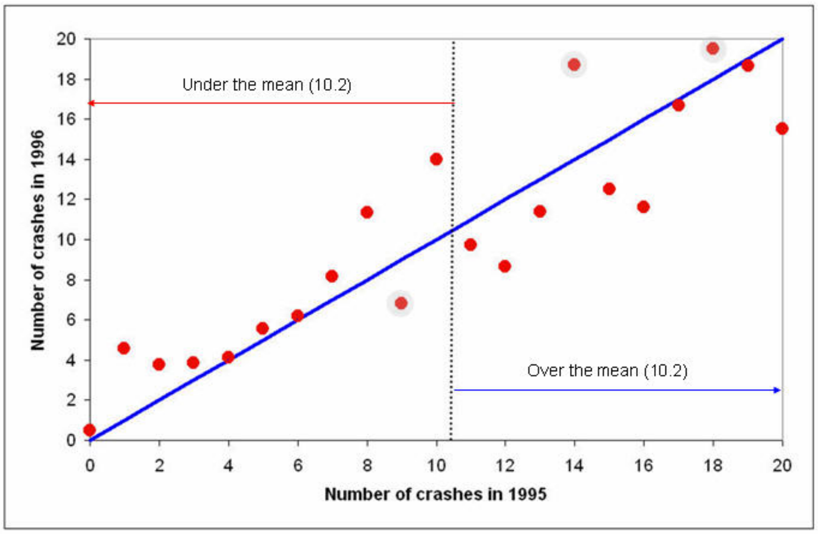

Figure 30: Example for RTM phenomenon of crash data in Scottsdale

Why should the RTM phenomenon be considered in safety studies? The short answer is that the ability to obtain an unbiased estimate of π is desired. Suppose that a red light camera is installed at one of five intersections whose number of crashes was 16 (K_{95}=16) because of a high crash history in 1995. In this case, the value of K_{96} (i.e., π) is not known, but the observed value in 1996 can be thought of as the expected value of the crash frequency in the after period (i.e., it is the estimate of λ). However, the value of K_{95} is not a reliable estimate of π because of the RTM phenomenon. When sites are selected due to a high crash count for treatment (RLCs), regression to the mean causes overestimation of the effect of the RLC. Thus, using the estimate from the observed crash frequency in the before period (K) brings about what is called *RTM bias*. Generally, the decision to treat entities is based on their crash history, especially abnormally high crash histories—which makes engineering sense. According to the results of a survey (see Table 4), the installation of red light cameras was determined mainly by high crash frequency, even though citywide coverage or geographic conditions for hardware installation were also considered. Thus, the results of analysis on the basis of the observed crash frequency in the before period (K) is likely to suffer from RTM bias.

The relevant question is of course, "how can the RTM bias be corrected". It is accounted for by considering the expected value as well as the observed value. As shown in the above example, the best estimate of π is obtained by the combination of the expected count (based on crash history or comparison sites) and the observed count. In order to obtain the expected count, the crash frequency of intersections that have similar characteristics with RLC intersections are investigated. Here, the intersections are called a *reference population*. A reference population of entities is the group of entities that share the same set of traits as the entity in safety in which we take an interest (Hauer, 1997). In such circumstances, the best estimate of π is conditionally defined as E[κ|K]. In other words, the estimate of π consists of the expected value (κ) given observed crash count K. One can think of the observed crash frequency (K) as a *sample* and the expected value (κ) as a *prior*, or prior knowledge about the expected safety performance of the reference population. Thus, the best estimate of π is a posterior given sample (K), and uses Bayesian logic. The Bayesian theorem is expressed as follows:

$$f(\kappa \mid K) = \frac{f(K \mid \kappa) \cdot f(\kappa)}{f(K)} \quad [8]$$

where $f(\kappa \mid K)$ is the posterior density of parameter κ given sample K , $f(\kappa)$ is the prior density of parameter (κ) in which κ is considered as a random variable, and $f(K \mid \kappa)$ is the likelihood of sample K. Suppose that the distribution of sample K and parameter κ are Poisson and Gamma distributed respectively. That is, 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*. Then, the posterior density of κ given K is calculated using the Bayesian theorem.

For a random sample of one intersection, the likelihood of the sample element, given κ, is

$$f(K \mid \kappa) = \frac{e^{-\kappa} \cdot \kappa^{K}}{K!}$$

The prior distribution for κ is a Gamma distribution with parameters *a* and *b*,

$$f(\kappa) = \frac{a^{b}}{\Gamma(b)} \cdot \kappa^{b-1} \cdot e^{-a\kappa}$$

where *a* and *b* are chosen depending on the exact knowledge or the degree of belief we have about the value of κ. In addition, the parameters are denoted as follows:

$$a = \frac{E[\kappa]}{V[\kappa]}, \quad b = \frac{E^{2}[\kappa]}{V[\kappa]} \quad [9]$$

The joint density of the sample (K) and κ is

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

and the marginal density of the sample (K) is

$$\begin{aligned} f(K) &= \int_0^\infty f(K \mid \kappa) \cdot f(\kappa)\, d\kappa \\ &= \frac{a^b}{K! \cdot \Gamma(b)} \int_0^\infty e^{-(a+1)\kappa} \cdot \kappa^{(K+b-1)}\, d\kappa \\ &= \frac{a^b \cdot \Gamma(K+b)}{K! \cdot \Gamma(b) \cdot (a+1)^{K+b}} \end{aligned}$$

In conjunction with "the joint density of the sample (K) and κ" and "the marginal density of the sample (K)", the posterior density for κ is

$$\begin{aligned} f(\kappa \mid K) &= \frac{f(K \mid \kappa) \cdot f(\kappa)}{f(K)} \\ &= \frac{(a+1)^{K+b}}{\Gamma(K+b)} \cdot \kappa^{(K+b-1)} \cdot e^{-(a+1)\kappa} \end{aligned}$$

and we see that the posterior density for κ is a Gamma distribution with parameters a+1 and K+b. As a result, the Bayesian expected value of κ and the Bayesian variance of κ are obtained:

$$E[\kappa \mid K] = \frac{K+b}{a+1},\ V[\kappa \mid K] = \frac{K+b}{(a+1)^2}$$

By plugging parameters a and b expressed by E[κ] and V[κ] in the prior distribution of κ (Equation [9]), they are rewritten as follows:

$$E[\kappa \mid K] = w \cdot E[\kappa] + (1-w) \cdot K \qquad [10]$$

$$V[\kappa \mid K] = (1-w) \cdot E[\kappa \mid K] \qquad [11]$$

where the term w is a weight between 0 and 1.

$$w = \frac{E[\kappa]}{E[\kappa] + V[\kappa]} = \frac{1}{1 + \dfrac{V[\kappa]}{E[\kappa]}} \qquad [12]$$

In Equation [10], E[κ|K] is interpreted as the expected count of crashes for a site given observed crash frequency K, and E[κ] is the average crash frequency of similar intersections (i.e., the reference population). In addition, V[κ|K] is the variance of crashes for an intersection given observed crash frequency K. They are determined after obtaining the weight term shown in the equation [12]. The weight (w) consists of the average crash frequency of similar intersections (i.e., E[κ]) and the variation around E[κ] (i.e., V[κ]). If w is estimated to be near 1, then the E[κ|K] of the intersection of interest is close to the mean of its reference population (E[κ]). On the contrary, if w is estimated to be near 0, then the

E[κ|K] of the intersection of interest is mainly affected by the observed crash frequency (K). Thus, the estimate for E[κ|K] is always between K and E[κ].

In estimating Bayesian estimates, the two components, E[κ] and V[κ], play a pivotal role in obtaining the Bayesian estimator E[κ|K]. They are estimated because E[κ] and V[κ] are unknown parameters. As shown in Equation [8], the posterior density consists of two density functions: the joint density of likelihood and prior and the marginal density of the sample. Now, E[κ] and V[κ] are not known. In other words, the parameter of the prior is unknown because the parameters *a* and *b* of the prior consist of E[κ] and V[κ]. In the Bayesian approach, the actual data are used to estimate the parameters of the prior. Because data and not a set of theories or subjective beliefs are used, the approach is called the *Empirical Bayesian approach or method*. The name "Empirical Bayes" arises from the fact that the prior distribution is estimated from the actual data (Carlin and Louis, 2000).

The average crash frequency of the "reference population" and the variation around this average are brought into the Empirical Bayesian (hereafter EB) procedure through the Safety Performance Functions. The SPFs are calibrated from data using statistical techniques. In the calibration, it is common to assume that the crash frequencies serve as data from a negative binomial distribution (Hauer, 2001). By using a negative binomial regression model, E[κ] and V[κ] are easily estimated as follows:

$$\hat{E}[\kappa] = f(\text{covariates}) \qquad [13]$$

$$\hat{V}[\kappa] = \frac{\hat{E}^2[\kappa]}{b} = \hat{E}^2[\kappa] \cdot \alpha \qquad [14]$$

The estimate of E[κ] is the predicted value from a negative binomial regression model under the assumption that the covariates included in the regression capture the main safety related traits of the reference population (e.g. intersections suitable for RLCs). In addition, the estimate of V[κ] is taken from the variance structure of a negative binomial regression model (V[K]=E[κ]+V[κ]). In the equation [14], *b* is the parameter of the prior Gamma distribution, and α is the over-dispersion parameter of a negative binomial regression model that is equal to the inverse of parameter *b*.

By using these estimators, the estimated weight is calculated as follows:

$$\hat{w} = \frac{1}{1 + \alpha \cdot \hat{E}[\kappa]}\,. \qquad [15]$$

Finally, using the estimate of weight (Equation [15]) and the estimate of E[κ] and V[κ] (Equations [13] and [14]), the Bayesian estimate, E[κ |K] is estimated. Recall that the Bayesian estimate is considered for obviating RTM bias. As a result, the problem called RTM bias that is common in safety studies is adjusted using the Empirical Bayesian method, and the EB estimate is used to obtain π. In the next section, the correction in the 4-step process is described with the EB estimate.

Correction in 4-step for EB Method

In conjunction with EB estimate, the 4-step process to estimate the index of effectiveness (θ) and the change in safety (δ) is corrected. The following changes are made to the 4-step process previously described in detail.

Step 1: Estimate λ and predict π

The first step is to estimate λ and predict π. As before, the estimate of λ is equal to the sum of the observed number of crashes in the after period,

$$\hat{\lambda} = \sum_{i=1}^{5} l_i = L \ .$$

In the EB approach, the prediction of π is equal to the EB estimate. Note that the expected value is obtained from a statistical model, which accounts for traffic and potentially other safety related factors as well. As a result, the estimate of π is

$$\hat{\pi} = \hat{E}[\kappa \mid K] = \hat{w} \cdot \hat{E}[\kappa] + (1 - \hat{w}) \cdot K \ .$$

Step 2: Estimate $\hat{\sigma}^2[\hat{\lambda}]$ and $\hat{\sigma}^2[\hat{\pi}]$

The estimate of variance for $\hat{\lambda}$ is $\widehat{VAR}[\hat{\lambda}] = L$ under the assumption it is a Poisson distribution, and the estimate of variance for $\hat{\pi}$ is equal to the estimate of variance of EB estimate,

$$\widehat{VAR}[\hat{\pi}] = \hat{V}[\kappa \mid K] = (1 - \hat{w}) \cdot \hat{E}[\kappa \mid K] \ .$$

The remaining steps (steps 3 and 4) proceed as before. Table 59 shows the corrected 4-step process used in the EB method.

Table 59: Corrected 4-step for EB before-after study

Step	Goals	Formulas for before-and-after study with EB
Step 1	Estimate λ and predict π	$\hat{\lambda} = L$ $\hat{\pi} = \hat{E}[\kappa \mid K] = \hat{w} \cdot \hat{E}[\kappa] + (1 - \hat{w}) \cdot K$
Step 2	Estimate $\hat{\sigma}^2[\hat{\lambda}]$ and $\hat{\sigma}^2[\hat{\pi}]$	$\hat{V}AR[\hat{\lambda}] = L$ $\hat{V}AR[\hat{\pi}] = \hat{V}[\kappa \mid K] = (1 - \hat{w}) \cdot \hat{E}[\kappa \mid K]$
Step 3	Estimate δ and θ	$\hat{\delta} = \hat{\pi} - \hat{\lambda}$ $\hat{\theta} \cong \dfrac{\left(\dfrac{\hat{\lambda}}{\hat{\pi}}\right)}{\left(1 + \dfrac{\hat{V}AR[\hat{\pi}]}{\hat{\pi}^2}\right)}$
Step 4	Estimate $\hat{\sigma}^2[\hat{\delta}]$ and $\hat{\sigma}^2[\hat{\theta}]$	$\hat{\sigma}^2[\hat{\delta}] = \hat{\pi} + \hat{\lambda}$ $\hat{\sigma}^2[\hat{\theta}] \cong \dfrac{\hat{\theta}^2 \cdot \left[\dfrac{\hat{V}AR(\hat{\lambda})}{\hat{\lambda}^2} + \dfrac{\hat{V}AR(\hat{\pi})}{\hat{\pi}^2}\right]}{\left[1 + \dfrac{\hat{V}AR(\hat{\pi})}{\hat{\pi}^2}\right]^2}$

Prediction in EB before-after study

In this section the results of predicted values of π are summarized. As mentioned previously, they are calculated using an over-dispersion parameter (denoted as α) and the expected count obtained from SPFs (using a negative binomial regression model). Due to the importance of SPFs in the EB procedure, NBRMs are improved by adding additional predictor variables in order to better represent the reference population as much as possible. Additional variables include the number of lanes, average yellow clearance time. Predictions are performed for both target approaches and all approaches as was done previously.

Prediction Results: All Approaches

In the case of all approaches, the SPFs have additional independent variables. The estimation procedure is the same as those in the traffic flow correction section. In the prediction equations total AADT is divided into $AADT_{maj}$ and $AADT_{min}$. As mentioned previously, the total number of lanes and average yellow clearance time are considered as additional predictor variables. Table 60 shows the estimated SPFs and their associated parameter estimates along with the over-dispersion parameters.

Table 60: Results of the estimated SPFs for all approaches

Variable	Total	Angle	Left-turn	Rear-end
Constant	-9.763235	-2.415785	-1.615345	-15.13919
Ln(AADT)		0.2510904		
Ln($AADT_{maj}$)	0.95076974		0.1867004	1.465297
Ln($AADT_{min}$)	0.2945258		0.0933132	0.7799403
Number of Lanes	-0.10082			-0.2879134
Average Yellow timing				-0.9092048
Over-dispersion (α)	0.0706691	0.00000264	0.4116516	0.1568783

In all estimated models, the signs for traffic flow such as AADT, $AADT_{maj}$, and $AADT_{min}$ are positive, while the coefficients associated with the number of lanes and average yellow clearance times are negative. Using these estimated SPFs, the weights (w) and the Bayesian estimates (E[κ|K]) are obtained, and the results are shown in Table 61.

Table 61: The results of weight and prediction in the EB estimation

Intersection ID	Total		Angle		Left-turn		Rear-end	
	w	E[κ|K]	w	E[κ|K]	w	E[κ|K]	w	E[κ|K]
S1	0.66	8.56	1.00	1.35	0.42	4.88	0.70	2.67
S2	0.54	10.95	1.00	1.60	0.37	2.59	0.45	7.17
S3	0.56	12.48	1.00	1.43	0.40	4.99	0.53	5.90
S4	0.56	11.48	1.00	1.58	0.38	5.00	0.49	5.78
S5	0.49	12.20	1.00	1.55	0.38	1.93	0.39	8.16
S6	0.54	12.69	1.00	1.58	0.37	4.07	0.50	6.11
S7	0.53	13.67	1.00	1.55	0.38	5.19	0.44	7.70
S8*	1.00	10.14	1.00	5.07	1.00	3.21	1.00	1.86
S9	0.54	11.53	1.00	1.54	0.38	2.37	0.68	4.77
S10	0.50	14.73	1.00	1.52	0.38	6.55	0.45	6.82
S11	0.50	15.36	1.00	1.54	0.38	3.57	0.41	10.36
S12	0.69	6.38	1.00	1.24	0.44	3.74	0.82	1.36
S13	0.63	8.73	1.00	1.39	0.41	3.05	0.67	3.80
S14	0.55	11.09	1.00	1.48	0.39	3.38	0.54	5.84

*Due to the lack of data, a Bayesian estimate could was not obtained.

Table 62: The number of crashes in the before-after study using EB estimates

Crash Types	K	$\hat{\pi}$ (Simple before-and-after)	$\hat{\pi}$ (EB before-and-after)	$\hat{\lambda}$
Angle Crashes	207	162.6	135.5	113
Left-turn Crashes	457	281.4	276.5	167
Rear-end Crashes	676	397.3	406.0	590
Total	1340	841.2	822.1	870

Table 62 shows the number of crashes that result from the EB estimation. The estimates for angle and left-turn crashes are slightly reduced, while the estimate of rear-end crashes is slightly greater compared to the simple before-and-after study. Even though the RLC intersections were selected due to their observed high total crash frequencies, the number of rear-end crashes may not have been abnormally high (the calculations suggest they are slightly low on average). This is not surprising because presumably sites were selected due to the high RLR crashes, which typically are left-turn and angle crashes.

Prediction Results: Target Approaches

In the case of the target approaches, the SPFs estimated in the traffic flow correction section are used in spite of efforts to estimate improved multivariate SPFs with additional explanatory variables. Table 63 shows the weights and prediction results. For angle crashes, the Bayesian correction could not be applied due to the insignificant over-dispersion parameter. As a result, the estimates for angle crashes are equal to those in simple before-and-after study.

Table 63: The results of weight and prediction in the EB estimation

Intersection ID	Total		Angle		Left-turn		Rear-end	
	w	E[κ|K]	*w*	E[κ|K]	*w*	E[κ|K]	*w*	E[κ|K]
S1	0.60	5.12	-	5.9	0.44	3.88	0.67	0.82
S2	0.47	4.61	-	3.9	0.38	1.35	0.50	2.09
S3	0.55	5.71	-	3.7	0.45	2.97	0.43	2.49
S4	0.48	5.59	-	3.9	0.38	3.03	0.55	1.58
S5	0.49	4.74	-	7.9	0.40	1.08	0.42	2.72
S6	0.48	5.60	-	11.8	0.38	2.47	0.48	1.75
S7	0.49	7.40	-	7.9	0.39	4.52	0.47	2.30
S8*	1.00	6.59	-	19.6	1.00	3.04	1.00	1.01
S9	0.50	4.16	-	1.1	0.39	1.54	0.49	1.87
S10	0.51	6.80	-	1.9	0.40	4.48	0.51	1.95
S11	0.50	5.83	-	1.0	0.41	1.90	0.43	3.53
S12	0.66	2.85	-	0.4	0.45	2.19	0.81	0.43
S13	0.58	4.47	-	1.2	0.47	2.23	0.52	1.80
S14	0.53	4.56	-	0.6	0.39	1.95	0.68	1.36

*Due to the lack of dataset, the Bayesian estimate could not be applied.

Table 64 shows the number of crashes obtained from the EB analysis approach. The results follow the trends of the analysis for all approaches.

Table 64: The number of crashes in the before-after study with EB estimates

Crash Types	**K**	$\hat{\pi}$ **(Simple before-after)**	$\hat{\pi}$ **(EB before-after)**	$\hat{\lambda}$
Angle Crashes	91	76.8	76.8	62.0
Left-turn Crashes	308	202.7	192.8	106.0
Rear-end Crashes	199	116.5	130.4	184.0
Total	598	396.0	393.5	352.0

Analysis results: Change in safety and index of effectiveness

Again steps 3 and 4 were performed in order to estimate the change in safety and index of effectiveness. In addition, the variances for these parameters are estimated. Table 65 shows these results.

Table 65: Results of EB before-after study

Jurisdiction	Crash Types	Change in safety		Index of effectiveness	
		$\hat{\delta}$	$S[\hat{\delta}]$	$\hat{\theta}$	$S[\hat{\theta}]$
All Approaches	Angle Crashes	22.47	10.87	0.83	0.08
	Left-turn Crashes	109.51	14.19	0.60	0.05
	Rear-end Crashes	-184.04	25.10	1.45	0.06
	All Crashes	-47.90	30.78	1.06	0.04
Target Approach	Angle Crashes	14.76	12.37	0.80	0.14
	Left-turn Crashes	86.79	11.35	0.55	0.06
	Rear-end Crashes	-53.60	14.05	1.41	0.11
	All Crashes	41.51	19.77	0.89	0.05

When compared with the results of the simple before-and-after study, the effects of red light cameras on safety are slightly reduced by the application of EB method. In other words, the simple before-and-after study overestimates the effects of the RLCs on crashes. Figure 31 shows the 95% confidence intervals for indexes of effectiveness.

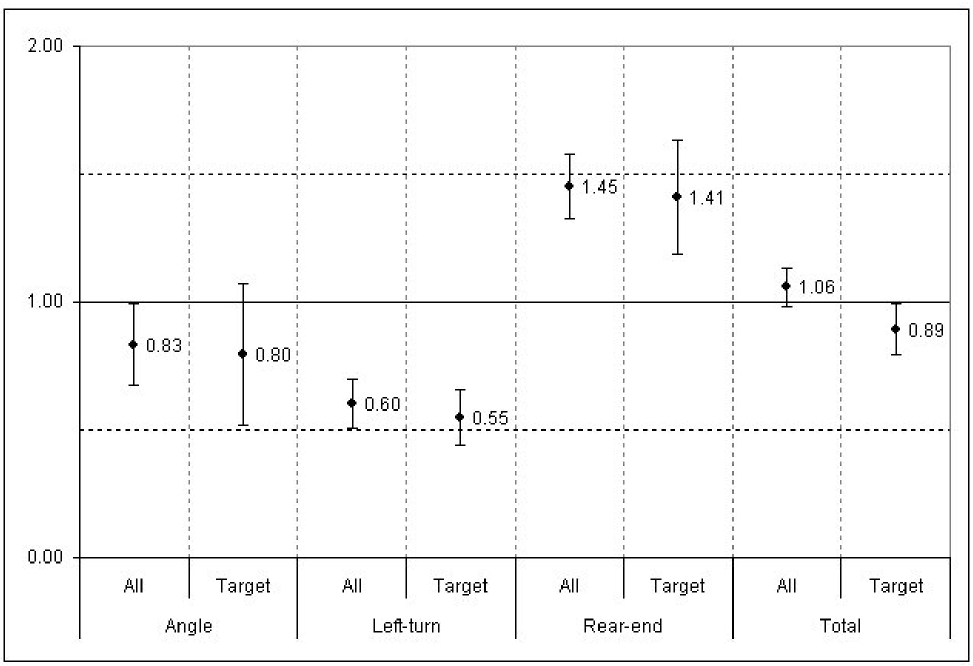

Figure 31: 95% CIs for indexes of effectiveness (Bayesian method)

Economic Analysis of the Safety Effects of RLCs

In this section the estimated changes in crashes are translated to economic impacts. From past research and the results of the evaluations conducted in this study, the installation of RLCs generally reduces angle crashes and left-turn crashes, while it generally increases rear-end crashes. Although the approximate 95% confidence intervals lead to lack of statistical significance, the expected values clearly indicate consistency and agreement with past findings. As is common with many studies of this nature, relatively small samples sizes and fairly “noisy” relationships between safety and roadway features lead to large standard errors. It is the consistency of findings across methods and agreement with past research that provides greater confidence in the expected values of δ and θ obtained in this research effort. As a result, the expected values and approximate 95% confidence intervals are used as “best” estimates of the expected impacts of RLCs in the state of Arizona.

Changes in severity by crash types

Before economic benefits can be quantified, the relationships between crash type and crash severity are needed for the cities of Phoenix and Scottsdale. Thus, crash data were categorized by crash type and disaggregated by severity. Then, simple duration ratio corrections are applied to this dataset (so comparisons are valid across different periods of observation). Table 66 shows the results of this analysis. The crash frequencies for target approaches by severity are shown using 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). Figure 32 reveals the percent changes in severities by crash types from the before to after periods.

Table 66: Crash frequency in before-after period by crash severity (target approaches)

Jurisdiction	Crash Type	Severity	Before		After	
			Crash frequency	%	Crash frequency	%
Phoenix	Angle and Left-turn	K+A+B+C	86.4	41.1%	85.0	37.8%
		O	71.9	34.2%	57.0	25.3%
	Rear-end	K+A+B+C	24.3	11.6%	33	14.7%
		O	27.5	13.1%	50	22.2%
	Total		210.1	100%	225.0	100%
Scottsdale	Angle and Left-turn	K+A+B+C	140.1	35.6%	74.0	21.0%
		O	136.5	34.7%	94.0	26.7%
	Rear-end	K+A+B+C	32.5	8.3%	46	13.1%
		O	84.1	21.4%	138	39.2%
	Total		393.1	100%	352.0	100%

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 crashes of rear-end crashes is greater than the increase in the proportion of fatality and injury crashes. For example, on target approaches in Scottsdale, the increase in the proportion of PDO rear-end crashes (0.83=(39.2-21.4)/21.4) is greater than the increase in the proportion of fatality and injury crashes (0.57=(13.1-8.3)/8.3). This finding suggests that

RLCs may change the proportion of crash severities at RLC intersections (since, for example, this same phenomenon is observed at Phoenix intersections).

As shown in Figure 32, the proportion reduction of severe angle plus left-turn crashes in Scottsdale (35.6% to 21%) is greater than the same reduction in Phoenix (41.1% to 37.8%). The changes in the proportion of PDO angle plus left-turn crashes are similar across the two cities. Thus, in summary, it appears that the RLCs in Scottsdale are resulting in less severe crashes, on average, then in Phoenix.

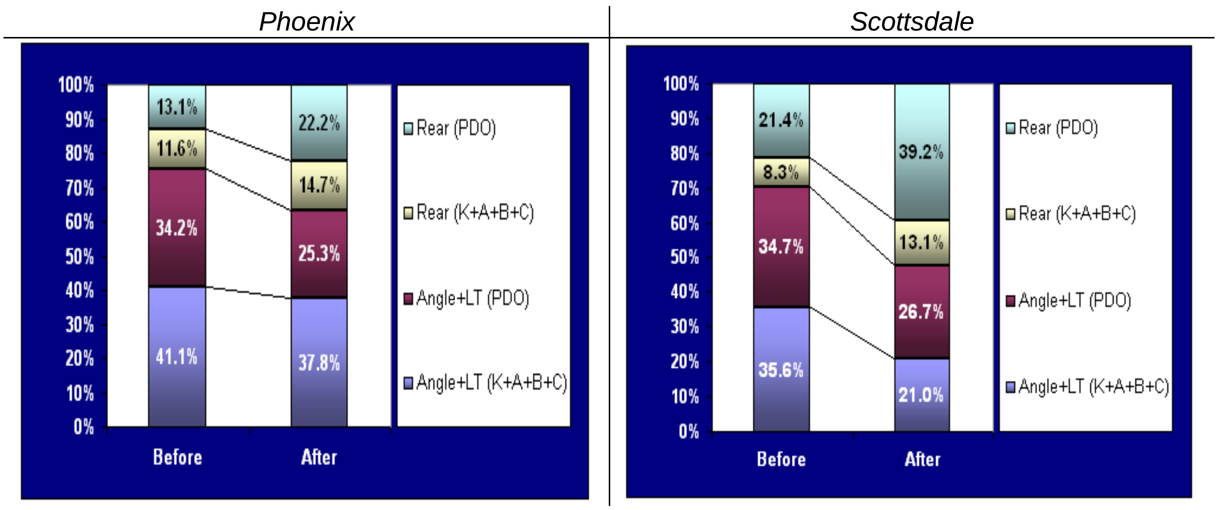

Figure 32: Percent change in severities by crash types (target approaches)

Table 67 shows the crash frequencies on all approaches by severity, and Figure 33 shows the changes in the portion of severities by crash types during the before and after periods. The same trends emerge for all approaches as for target approaches: the reduction in severe left-turn and angle crashes is significantly greater in Scottsdale than in Phoenix. PDO rear-end crashes consist of nearly half of all crashes after the RLC program in Scottsdale, whereas these same crashes represent less than a quarter of all crashes in Phoenix.

Table 67: Crash frequency in before-after period by crash severity (all approaches)

Jurisdiction	Crash Type	Severity	Before		After	
			Crash frequency	%	Crash frequency	%
Phoenix	Angle and Left-turn	K+A+B+C	151.0	37.6%	162.0	36.5%
		PDO	123.7	30.8%	120.0	27.0%
	Rear-end	K+A+B+C	53.9	13.4%	64	14.4%
		PDO	73.6	18.3%	98	22.1%
	Total		402.2	100%	444.0	100%
Scottsdale	Angle and Left-turn	K+A+B+C	217.7	26.1%	117.0	13.5%
		PDO	221.9	26.6%	163.0	18.8%
	Rear-end	K+A+B+C	125.4	15.1%	153	17.6%
		PDO	267.8	32.2%	436	50.2%
	Total		832.9	100%	869.0	100%

It is interesting to note that the proportions of crashes of any type do not change significantly in Phoenix; however, severe left-turn and angle crashes decrease and property damage crashes increase significantly in Scottsdale.

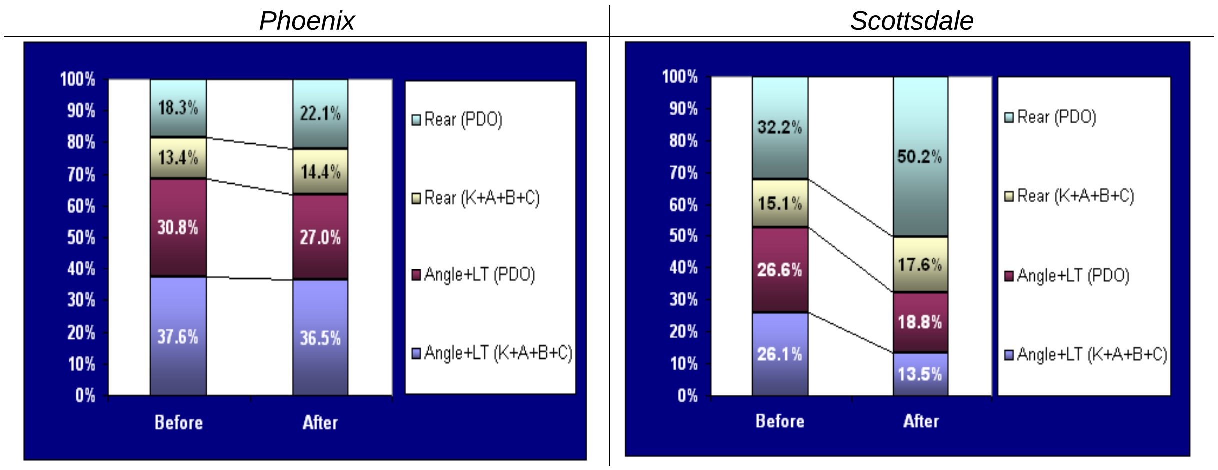

Figure 33: Percent change in severities by crash types

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.

Crash benefits of RLCs

The economic impacts resulting from RLCs are calculated as follows:

$$\text{Economic Benefits} = \sum_{i=1}^{t} (\hat{\delta}_i \cdot C_i) \qquad [16]$$

where C_i is the average crash cost of the ith severity category (i={1,…, t}) and the estimates of δ_i are the estimated changes in crashes 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. In order to make a comparison with other safety investments, such as the addition of turning lanes, additional enforcement, etc., the costs of RLC programs would need to be considered.

Crash costs and change in safety

Average crash costs are needed for the KABCO injury scale in order to proceed. Fortunately, average crash costs of red light camera programs were made available in previous research (Council *et al.*, 2005). The estimates of crash costs cited in Council *et al.* were obtained from the Pacific Institute for Research and Evaluation (PIRE), and are summarized in Table 68 for the KABCO injury scale.

Table 68: Per-crash cost estimates by severity level [source: Council et al, 2005]

Crash severity level	Estimated Crash Cost ($)	
	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

The crash costs are categorized by crash types as well as crash severities. Thus, if the sample size for each severity category is sufficient, all crash costs could be used to estimate crash benefits by each severity. However, 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). This same approach was employed in the study cited previously (Council *et al.*, 2005).

The estimated changes in crashes (δ's) derived from the various evaluation methods are shown in Tables 69 and 70. It is necessary, however, to estimate the changes in safety by crash severity category 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 types into the crashes by severities, the proportion of crashes with a certain severity for each crash type obtained from the observed data were calculated. This requires the assumption that the proportion is likely to remain constant, even though the estimates of π (i.e., the count of crashes in the after period) for each crash type are changed by corrections such as traffic flow, comparison ratio, or empirical Bayesian estimates. In other words, the assumption is that the corrections made for traffic, unobserved factors, and regression to the mean do not influence the expected distribution of crashes in the after period if the countermeasure is not installed.

Table 69: Summary of change in safety on all approaches: estimate (standard deviation)

Jurisdiction	Method	Angle	Left-turn	Rear-end	Total
Phoenix	Simple correction	5.28 (9.74)	-12.56 (19.05)	-34.52 (15.60)	-41.80 (26.48)
	Comparison correction	9.17 (7.79)	2.15 (15.19)	-27.27 (12.92)	-24.79 (21.18)
Scottsdale	Simple correction	49.59 (17.35)	114.41 (21.54)	-192.75 (31.52)	-28.75 (41.94)
	Traffic flow correction	47.24 (17.19)	113.45 (21.51)	-228.37 (34.53)	-57.39 (44.03)
	EB correction	22.47 (10.87)	109.51 (14.19)	-184.04 (25.10)	-47.90 (30.78)

Note: the estimates less than 0 indicate an increase in crashes.

Table 70: Summary of change in safety on target approaches: estimate (standard deviation)

Jurisdiction	Method	Angle	Left-turn	Rear-end	Total
Phoenix	Simple correction	12.09 (6.38)	4.19 (14.26)	-31.19 (10.79)	-14.91 (18.99)
	Comparison correction	14.46 (4.89)	13.01 (11.24)	-27.97 (9.35)	-6.05 (15.15)
Scottsdale	Simple correction	14.76 (12.37)	96.73 (18.06)	-67.50 (17.40)	43.99 (27.96)
	Traffic flow correction	11.46 (12.18)	94.84 (17.95)	-75.31 (17.90)	35.24 (28.55)
	EB correction	14.76 (12.37)	86.79 (11.35)	-53.60 (14.05)	41.51 (19.77)

From the results of the simple correction used in the previous subsection, the portion of crash severities in each crash type are calculated and summarized in Tables 71 and 72.

Table 71: The proportion of crash severities in two crash types (Phoenix)

Severities	Angle+ Left-turn crashes		Rear-end crashes	
	Target approaches	All approaches	Target approaches	All approaches
Fatality (K)	0.82%	0.71%	0.00%	0.00%
Incapacitating Injury (A)	7.69%	7.65%	0.00%	0.51%
Non-incapacitating Injury (B)	18.28%	19.19%	6.14%	6.95%
Possible Injury (C)	27.84%	27.49%	40.77%	34.82%
Property Damage Only (O)	45.37%	44.95%	53.09%	57.72%
K+A+B+C	54.63%	55.05%	46.91%	42.28%

Table 72: The proportion of crash severities in two crash types (Scottsdale)

Severities	Angle+ Left-turn crashes		Rear-end crashes	
	Target approaches	All approaches	Target approaches	All approaches
Fatality (K)	0.71%	0.47%	0.00%	0.00%
Incapacitating Injury (A)	14.07%	13.67%	1.58%	4.42%
Non-incapacitating Injury (B)	14.27%	15.91%	5.27%	5.15%
Possible Injury (C)	21.60%	19.47%	21.00%	22.33%
Property Damage Only (O)	49.34%	50.48%	72.15%	68.11%
K+A+B+C	50.66%	49.52%	27.85%	31.89%

By applying the proportions in Tables 71 and 72 to the crash dataset, the change in safety (δ) is recalculated as shown in Tables 73 and 74. As defined, the estimates of δ are the predicted value of π minus λ, and $S\left[\hat{\delta}\right]$ is the standard deviation. Unlike the estimates in Tables 69 and 70 (change in safety during all after periods), the estimates in Tables 73 and 74 are the expected changes in safety per year. Then, Equation [16] is applied to the estimation of crash benefits by using the change in safety shown in Tables 73 and 74 as well as the crash costs in Table 68.

Care should be taken to interpret these tables. Target approaches typically represent one approach per intersection, whereas all approaches typically represent four approaches at an intersection. Thus, if the effects of RLCs are equal on target and all approaches, the effect size for all approaches would be expected to be 4× that for target approaches. In other words, if PDO angle and left-turn crashes increased by two crashes, then for an "equal" effect eight additional crashes would be expected on all approaches.

Table 73: Summary of reduction in crashes per year recalculated by severity (Phoenix)

Method	Type/ severity	Angle and LT		Rear-end	
		KABC	PDO	KABC	PDO
Target approaches	Simple correction	0.68 (9.97)	7.37 (8.70)	-4.48 (5.71)	-11.80 (6.60)
	Comparison correction	3.78 (6.94)	9.94 (5.76)	-3.73 (4.36)	-10.94 (5.31)
All approaches	Simple correction	-5.80 (13.43)	1.63 (11.87)	-5.55 (8.23)	-12.77 (9.88)
	Comparison correction	-0.59 (9.42)	5.88 (8.13)	-4.01 (5.95)	-10.67 (7.31)

Note: estimates less than 0 (shown as negative values) indicate an increase in crashes.

Table 74: Summary of reduction in crashes per year recalculated by severity (Scottsdale)

Method	Type/ severity	Angle and LT		Rear-end	
		KABC	PDO	KABC	PDO
Target approaches	Simple correction	13.47 (13.15)	5.50 (13.06)	-2.26 (6.47)	-7.02 (10.48)
	Traffic flow correction	13.21(12.98)	5.25 (12.90)	-2.57 (6.85)	-7.82 (11.08)
	EB Correction	12.45 (8.45)	4.54 (8.64)	-1.74 (3.55)	-5.66 (5.83)
All approaches	Simple correction	20.62 (16.01)	10.55 (16.78)	-2.05 (12.13)	-21.48 (18.99)
	Traffic flow correction	20.57 (15.90)	10.50 (16.67)	-3.43 (14.38)	-24.71 (22.35)
	EB Correction	18.29 (6.27)	8.09 (7.26)	-2.75 (6.19)	-23.13 (10.30)

Results of crash benefits

In this subsection, the results of crash benefits are described. Tables 75 and 76 show the mean crash benefits (per year) as well as the lower and upper approximate 95% confidence interval of crash benefits of the reduction in crashes (i.e., $\hat{\delta} \pm 1.96 \cdot S[\hat{\delta}]$). Estimates with negative values are costs, while estimates with positive values are benefits. For example, the expected benefit of angle and left-turn crashes for serious injury crashes in Phoenix is about $43,862 for all target approaches in Phoenix using the naïve approach, and $243,686 using the comparison group approach that accounts for measured and unmeasured factors.

Table 75: Crash benefits per year in Phoenix ($/year)

	Crash types	Severity	Target approaches			All approaches		
			Lower	Mean	Upper	Lower	Mean	Upper
Simple correction	Angle and LT	KABC	-$1,215,688	$43,862	$1,303,411	-$2,071,079	-$374,004	$1,323,072
		PDO	-$84,030	$63,891	$211,812	-$187,650	$14,147	$215,944
	Rear-end	KABC	-$840,974	-$240,538	$359,897	-$1,163,600	-$297,808	$567,984
		PDO	-$283,582	-$135,211	$13,159	-$368,443	-$146,358	$75,727
	Angle and LT		-$1,299,718	$107,752	$1,515,223	-$2,258,729	-$359,857	$1,539,016
	Rear-end		-$1,124,556	-$375,750	$373,056	-$1,532,043	-$444,166	$643,711
	Total		-$2,424,274	-$267,997	$1,888,279	-$3,790,773	-$804,023	$2,182,727
Comparison correction	Angle and LT	KABC	-$633,144	$243,686	$1,120,516	-$1,228,736	-$38,275	$1,152,187
		PDO	-$11,716	$86,217	$184,150	-$87,189	$51,026	$189,242
	Rear-end	KABC	-$658,309	-$199,991	$258,327	-$840,874	-$215,295	$410,285
		PDO	-$244,749	-$125,408	-$6,067	-$286,618	-$122,294	$42,030
	Angle and LT		-$644,859	$329,903	$1,304,666	-$1,315,925	$12,752	$1,341,428
	Rear-end		-$903,058	-$325,399	$252,260	-$1,127,492	-$337,588	$452,315
	Total		-$1,547,917	$4,504	$1,556,926	-$2,443,417	-$324,836	$1,793,744

On the target approaches, the mean crash benefit for total crashes using the comparison correction is $4,504/year, while the simple or naïve before-and-after approach produces a net cost of the program. The comparison correction resulted in a prediction π that increased slightly, translating to a slightly larger estimate of RLC effectiveness.

It is interesting to note that the net benefit estimated using the naïve approach is negative even though the angle/LT crashes are reduced (the reduction in crashes is 8.05 = 0.68 + 7.37: see Table 73). In this case, if the entire reduction in angle/LT crashes belonged to the KABC severity level, the crash benefit from angle/LT crashes would be $518,967 (8.05*$64,468), indicating a positive net benefit ($143,217=$518,967-$375,750). However, the reduction in angle/LT crashes mostly results from a reduction in PDO crashes. As a result, the crash benefits from angle/LT are relatively small and the net benefit is negative, indicating that the benefits from angle/LT crashes do not exceed the costs from rear-end crashes.

On all approaches, the net benefits from both evaluation methods are negative, indicating that the benefits from angle/LT crashes do not exceed the costs from rear-end crashes. Like the results on target approaches, the RLCs in Phoenix contribute more to reducing PDO crashes than to decreasing fatality and injury crashes in angle/LT crashes, and they contribute more to increasing PDO crashes than to increasing fatality and injury crashes in rear-end crashes.

Table 76: Crash benefits per year in Scottsdale ($/year)

	Crash types	Severity	Target approaches			All approaches		
			Lower	Mean	Upper	Lower	Mean	Upper
Simple correction	Angle and LT	KABC	-$793,350	$868,352	$2,530,055	-$693,144	$1,329,479	$3,352,102
		PDO	-$174,268	$47,685	$269,638	-$193,737	$91,499	$376,734
	Rear-end	KABC	-$801,846	-$121,142	$559,562	-$1,386,059	-$109,940	$1,166,179
		PDO	-$315,939	-$80,420	$155,099	-$672,892	-$246,259	$180,375
	Angle and LT		-$967,618	$916,037	$2,799,693	-$886,881	$1,420,977	$3,728,836
	Rear-end		-$1,117,785	-$201,562	$714,661	-$2,058,952	-$356,199	$1,346,554
	Total		-$2,085,402	$714,476	$3,514,354	-$2,945,833	$1,064,779	$5,075,390
Traffic flow correction	Angle and LT	KABC	-$788,770	$851,450	$2,491,671	-$682,921	$1,326,354	$3,335,630
		PDO	-$173,667	$45,539	$264,744	-$192,373	$91,055	$374,483
	Rear-end	KABC	-$857,871	-$137,872	$582,128	-$1,696,245	-$184,184	$1,327,878
		PDO	-$338,672	-$89,696	$159,279	-$785,440	-$283,305	$218,830
	Angle and LT		-$962,437	$896,989	$2,756,415	-$875,294	$1,417,409	$3,710,113
	Rear-end		-$1,196,543	-$227,568	$741,407	-$2,481,685	-$467,488	$1,546,708
	Total		-$2,158,980	$669,421	$3,497,822	-$3,356,979	$949,921	$5,256,821
Empirical Bayesian correction	Angle and LT	KABC	-$265,397	$802,777	$1,870,952	$386,490	$1,179,172	$1,971,853
		PDO	-$107,544	$39,357	$186,259	-$53,276	$70,164	$193,604
	Rear-end	KABC	-$466,849	-$93,119	$280,612	-$798,437	-$147,750	$502,937
		PDO	-$195,756	-$64,882	$65,993	-$496,556	-$265,125	-$33,695
	Angle and LT		-$372,941	$842,135	$2,057,210	$333,214	$1,249,336	$2,165,458
	Rear-end		-$662,606	-$158,001	$346,604	-$1,294,993	-$412,875	$469,242
	Total		-$1,035,547	$684,134	$2,403,815	-$961,779	$836,460	$2,634,700

In Scottsdale the crash benefits from rear-end crashes are negative due to the increase in rear-end crashes during the after period. On all approaches, the mean crash benefit from total crashes (a net benefit) using the empirical Bayesian correction is $836,460 per year. This estimate reflects that the benefits from the reduction of angle/LT crashes ($1,249,336) exceeds the costs from the increase in rear-end crashes ($412.875). On target approaches, the net benefit is $684,134 per year. The magnitude of the net benefit on target approaches is less than on all approaches. This finding suggests that the net benefit on target approaches is significantly larger than benefits on non-RLC approaches. For example, if the net benefit on all approaches is distributed evenly to each approach at a 4-leg intersection the RLC would affect each approach evenly, and the resulting net benefit would be $209,115 ($836,460/4) on each approach. As shown in the table, the net benefit on target approaches is significantly higher. It can be concluded that RLCs in Scottsdale contribute more to reducing fatality and injury crashes than to decreasing PDO angle/LT crashes, and the increase in rear-end crashes mainly resulted in increases in PDO crashes.

General Operating Costs of RLCs

In this section, the general operating costs of RLCs are provided. There are three types of cameras available for red light running enforcement: 35-mm wet film cameras, digital cameras, and video cameras. Most implementations use 35-mm wet film cameras, although there is a growing trend toward the use of digital cameras (Quiroga *et al*, 2003).

Thirty-five millimeter wet film cameras are the most commonly used type of red light cameras. The cameras are usually placed atop poles or bars equipped with mechanical gears or bearings that enable the raising and lowering of the cameras for maintenance and/or for replacing the film. Most systems produce black-and-white photographs, although some systems also produce color photographs. While black-and-white photographs offer better resolution, contrast, and are less expensive than color photographs, color photographs can more clearly confirm the traffic signal was displaying red at the time of the violation. The cost of a 35-mm wet film camera system is around $50,000–$60,000. This cost includes installation and associated equipment (pole, loop detectors, and camera). Monthly operating costs are approximately $5,000 per camera system (Maccubbin *et al*, 2001).

The use of digital cameras for red light running enforcement is increasing. Like their 35-mm wet film camera counterparts, digital cameras are placed atop poles or masts. However, they do not need to be accessed as frequently as wet film cameras, which can result in lower operating costs. Digital cameras are increasing in popularity due to improvements in technology that enable better resolution photographs than older digital systems, better definition of vehicles and license plates, and reduction of problems associated with smears and reflections from headlights. Digital camera systems are usually more expensive than wet film camera systems (up to $100,000) (Maccubbin *et al*, 2001).

It has been reported at various informal presentations about RLCs that the systems can be run as revenue neutral operations. Specifically, fines are set such that given the adjudication rate and red light running violation rates, the revenue generated is equal to the operating costs of the system. However, it has been difficult to find widespread published estimates of RLC installation and operating costs.

Maximum expected crash benefits

So far the report has focused on average effects for RLC systems—one each in the cities of Scottsdale and Phoenix. Of course a vital question has been whether or not the RLC systems in these cities, as a collection of intersections, are performing well. Much of the report 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?

As one might expect there are many factors that affect crashes at intersections, including the presence of RLCs. Thus we would expect, *a priori*, to observe differences in the statistical parameters across the intersections examined. For example, the index of effectiveness, θ, is not constant across intersections. RLCs may be very effective at some intersections and ineffective at others. Thus, it is interesting to examine the maximum expected benefit and the variability in benefits across observed intersections.

In this subsection, maximum expected crash benefits are investigated. The net crash benefits vary across RLCs intersections due to differences in characteristics of driver population, geometric design features, and other factors. Figure 34 shows a box plot of the crash benefits on target approaches across the two jurisdictions. The data are derived from the results of a comparison correction (Phoenix) and empirical Bayes' correction (Scottsdale). The boxplot shows the largest observation, the upper quartile, the median (e.g., $16,401), the lower quartile, and the smallest observation. Inspection of the plot reveals several interesting observations. First, although the median crash benefit is higher in Scottsdale, the maximum observed benefit is higher in Phoenix. It also shows that the variability of performance is much greater in Phoenix than in Scottsdale, with a very large negative benefit observed in Phoenix. Finally, the inter-quartile range and 25% and 75% values are not too dissimilar across the cities.

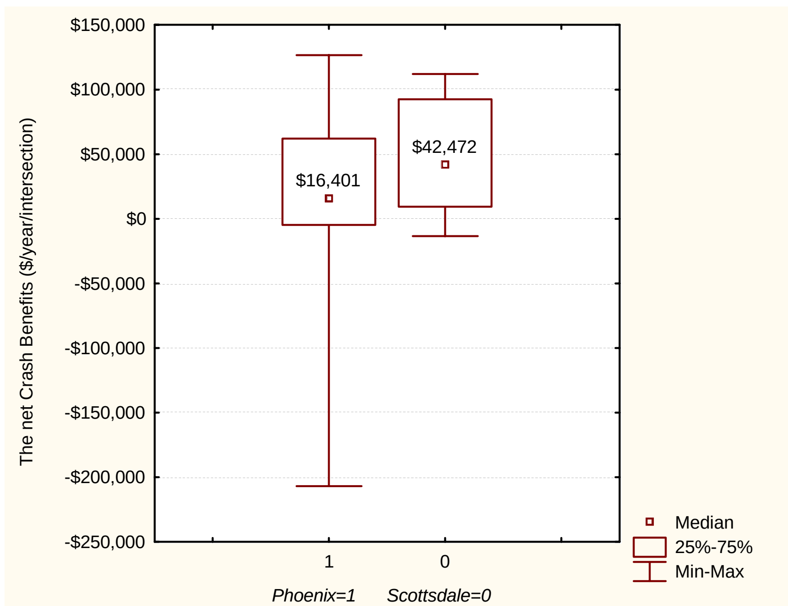

Figure 34: Box plots for crash net benefits on target approaches

Table 77 shows the descriptive statistics for the net crash benefits. The table reinforces observations in Figure 34: the mean is heavily skewed by the negatively performing intersections in Phoenix. The maximum estimated benefit is higher in Phoenix, suggesting that Phoenix has the best performing RLC intersection (it also has the worst performing RLC intersection as revealed by the minimums).

Table 77: Descriptive statistics for the net crash benefits on target approaches

Statistics	Phoenix	Scottsdale
Mean	450.42	48,866.72
Standard Error	33,403.41	11,851.44
Median	16,400.87	42,471.52
Standard Deviation	105,630.85	44,344.01
Sample Variance	11,157,875,575.05	1,966,391,539.95
Range	333,664.12	125,361.54
Minimum	-206,987.32	-13,447.36
Maximum	126,676.80	111,914.18
Sum	4,504.16	684,134.12
N	10	14

Table 78 shows the maximum expected net crash benefits in the two jurisdictions on a directly comparable basis ($/year/ intersection). As shown in the table, even though the central tendencies (i.e., median or mean) of the effects appear to be different, the maximum expected net crash benefits are similar. Thus, even though the system average benefit for the collection of 10 intersections in Phoenix is relatively less, the "best" intersections appear to function quite similarly in the two jurisdictions.

Table 78: The maximum expected net crash benefits ($/year/intersection)

Approaches	Phoenix	Scottsdale
Target approaches	$99,150	$106,765
All approaches	$218,474	$197,624

Factors affecting the performance of individual RLC intersections

The report has shown that as a system the Scottsdale intersections are performing well relative to Phoenix. In the previous section it was revealed that the system performances are heavily weighted by poorly performing intersections, and that the "best" intersections are similar in both Scottsdale and Phoenix. These results, however, do not yet shed light on which individual intersections perform well with respect to RLC effectiveness and why.

This section examines individual intersections with respect to safety effects of RLCs. It must be noted that confidence intervals on the safety effect at a single intersection are relatively large because of the small sample sizes (compared to say a group of intersections instrumented with RLCs within a city). There are no claims made as to the precision of the results obtained in this section, but instead agreement with past results, reasonableness, and consistency across multiple intersections are used to defend and explain the results. The careful analyst must recognize that the results are preliminary with respect to statistical precision. In other words, the analysis proceeds as though the estimated mean effect is a reliable indicator of the performance of an intersection, even though the variance of the mean effect may be quite large.

The differences in disaggregated effects between intersections

It is necessary to investigate what factors influence safety at intersections instrumented with RLCs. Unfortunately, there has not been a comprehensive study of RLCs that has adopted an experimental design to provide suitable answers to this question (McGee and Eccles, 2003). A lack of research that can identify these factors is not surprising, because the experimental design requirements are extensive, the sample size requirements are large, and the study would be extremely expensive. To illustrate, consider a study aimed to isolate the influence of warning signs and their role in RLC effectiveness. This study would seek to answer whether or not using a sign that warns motorists of the cameras is more effective than not using a sign. This study would require a large sample of locations and the identification of control and RLC sites with and without warning signs that are similar in all other influence variables (McGee and Eccles, 2003). In the real world, as mentioned, it is seldom possible for an agency or an analyst to design experiments to isolate the impact of many possible factors. This difficulty in conducting rigorous experiments explains why the effects of RLCs are described as "not conclusive" in NCHRP Synthesis 310. The simple fact is many uncontrolled variables affect safety, and despite numerous studies on the subject conclusions are somewhat mixed.

How then, are "cause and effect" relationships examined? In the professional safety field, the knowledge of "cause and effect" has often been extracted from "observational studies" consisting of both before-and-after and cross-section designs. The difference between the two main designs is provided here for review (Hauer, 2005).

First there is the observational "before-and-after" study. It arises when a change or treatment has been implemented on a unit or group of units. The change in accident history and in the attributes of these units from before the treatment to after the treatment is used to estimate the change in safety attributable to the treatment. Second, there is the observational "cross-section" study. It arises when the attributes and accident history of units, some found with treatment (attribute) X and some found with treatment (attribute) Y, are used in an attempt to estimate the safety effect of the difference in treatment (or attribute) in question. The main distinction between these two kinds of observational studies is the before-and-after study "treatment" means that something has actually changed from "before" to "after", while in a cross-section study the element of change is not present; there exists only a contemporaneous difference in some attribute of interest that could have been different and is therefore loosely called "treatment". In other words, the cross-section design yields units with and without treatment while the before-and-after design yields units before and after treatment. The benefit of the before-and-after design is more confidence in homogeneity from the before to the after periods—giving greater confidence that the observed effect is due to treatment. This benefit has led to the general preference for the before-and-after design for evaluating countermeasures (compared to the cross-section design). It is more difficult to estimate the effect of treatment from data collected from a cross section design, although numerous factors can be examined at once (this is both a benefit and a drawback—other factors vary across sites and so there is confounding; however, factors vary across sites and so their non-independent effects can be estimated).

Consider an example using railroad crossing countermeasures. Figure 35 shows how the effects of two treatments (gate with crossbuck and flasher with crossbuck) using cross-section data are analyzed. It shows the effects of rail-highway grade crossings on safety based on about 200,000 public crossings in the U.S. (the study was performed originally by Mengert in 1980, but the results are cited from Hauer's study in 2005).

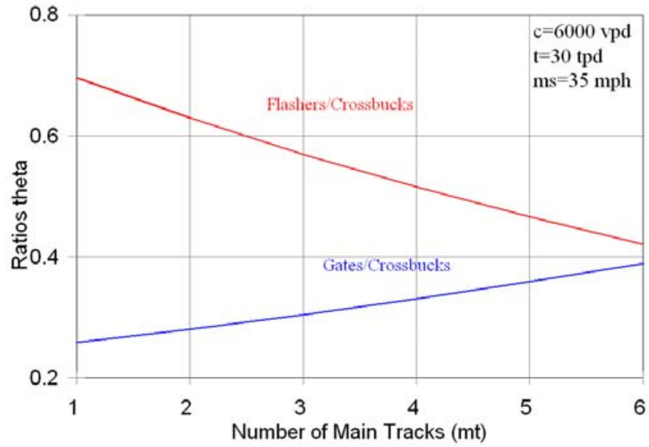

Figure 35: How the ratios θ vary with the number of main tracks [source: Hauer, 2005]

As shown in Figure 35, the effects of two different treatments vary with the number of main tracks. In the case of flasher with crossbucks, the effects tend to increase as the number of main tracks increase. On the contrary, the effects of gates with crossbucks tend to decrease with an increase in number of main tracks.

As shown in this example, it is possible to examine the influence of other factors on the effectiveness of RLCs when the number of samples is very large. Unfortunately, however, there are not enough samples (i.e., the RLCs intersections) to represent the range of influence of other influential factors. Note that the function of θ for rail-highway grade crossings is based on 200,000 crossings, but the number of RLCs intersections available for this study was 24. Alternatively, it is also possible to make θ a function of attributes in a before-and-after study. Again, however, in practice the number of entities on which a treatment is implemented is seldom sufficient for such distinctions to be made (Hauer, 2005). Thus, the problem in identifying factors that potentially affect the safety of RLC intersections results from both the lack of data and the inability to control numerous influential factors.

Despite the small sample sizes available, the following subsection examines the effects of various factors on safety at the RLC intersections examined in this study. The results should be viewed with caution, however, and follow-up study should be conducted to verify the results obtained in this analysis.

Data Description

In order to examine possible relationships between safety and other factors, a number of plausible variables were collected from on site investigations of the intersections in Phoenix and Scottsdale. These variables include signal phasing, intersection geometry, and operational variables. Figure 36 shows the histograms for data and Table 79 shows the descriptive statistics for these variables. In addition, the crash benefits estimated previously are summarized again in Table 80.

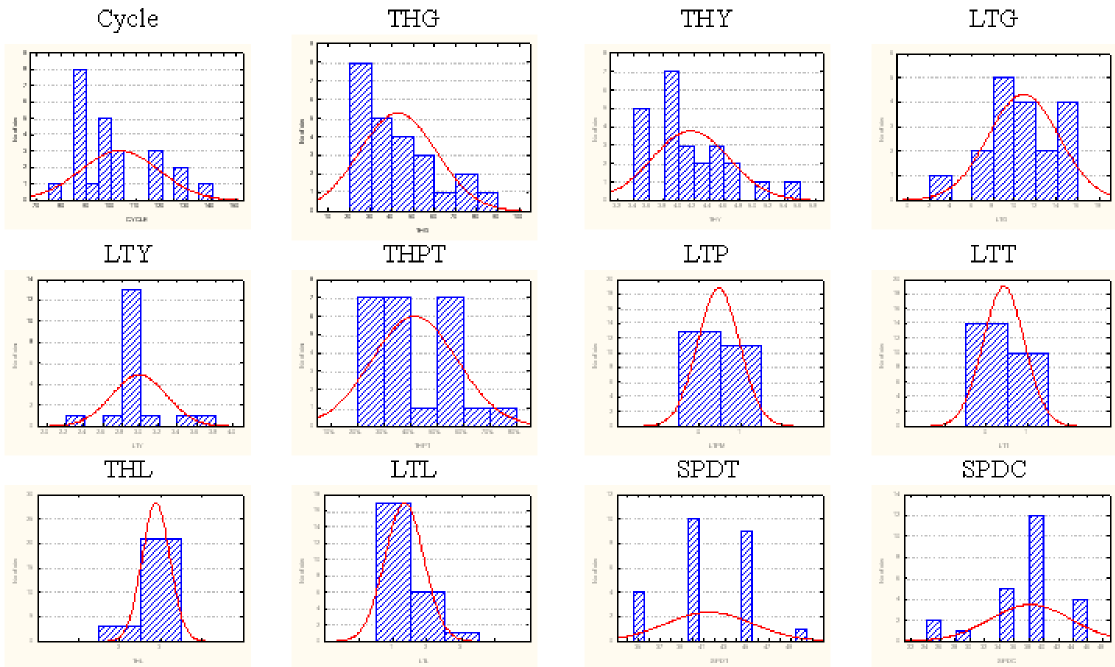

Figure 36: The histograms for the RLC intersection data

Table 79: Summary statistics for geometry, signal operation, and speed limits

Variables	Mean	Median	Mode	Stand. Dev.	Range	Min	Max	Description
Cycle	103	100	90	16	60	80	140	The length of cycle (sec)
THG	42.6	39.2	48.0	18.1	66.9	21.8	88.7	The length of green phase for through movements on target approach (sec)
THY	4.1	4.0	4.0	0.5	2.0	3.5	5.5	The length of yellow phase for through movements on target approach (sec)
LTG	10.8	10.6	-	3.3	13.0	3.0	16.0	The length of green phase for left-turn movements on opposing approach (sec)
LTY	3.0	3.0	3.0	0.3	1.5	2.3	3.7	The length of yellow phase for left-turn movements on opposing approach (sec)
LTP	0.5	0.5	1.0	0.5	1.0	0.0	1.0	The type of left-turn control on opposing approach (0: exclusively protected; 1: partially protected)
LTT	0.4	0.0	0.0	0.5	1.0	0.0	1.0	The type of left-turn control on opposing approach (0: lagging; 1: leading)
THPT	0.4	0.3	0.6	0.2	0.5	0.2	0.7	The portion of green phase for through movements on target approach over total cycle length
THL	2.9	3.0	3.0	0.3	1.0	2.0	3.0	Number of lanes for through movements on target approach
LTL	1.3	1.0	1.0	0.6	2.0	1.0	3.0	Number of lanes for left-turn movements on opposing approach
SPDT	41.5	40.0	40.0	4.0	15.0	35.0	50.0	The posted speed limits on target approach (mph)
SPDC	38.1	40.0	40.0	5.5	20.0	25.0	45.0	The posted speed limits on crossing approach (mph)
SPDdiff	3.8	0.0	0.0	5.6	20.0	0.0	20.0	The difference of posted speed limits between target approach and crossing approach (mph)

Note: N=24

Table 80: Summary statistics for crash benefits, cost, and net crash benefits on target app.

Statistics	Angle and LT($)	Rear-end ($)	Total($)
Mean	48,834.92	-20,141.65	28,693.26
Standard Error	13,273.22	9,351.92	15,906.09
Median	49,561.92	-7,232.29	31,200.19
Standard Deviation	65,025.25	45,814.87	77,923.63
Sample Variance	4,228,282,850.83	2,099,001,897.80	6,072,091,879.84
Range	314,881.19	245,964.59	333,664.12
Minimum	-138,765.56	-186,577.72	-206,987.32
Maximum	176,115.63	59,386.87	126,676.80
Sum	1,172,037.98	-483,399.70	688,638.28

Note: N=24

Relation between factors and crash benefits

The findings described in this section focus on those variables found to have a visible correlation with the expected (statistical mean) crash benefits shown in Table 80.

The effects of the length of cycle on the net crash benefits are illustrated in Figure 37. It indicates that expected crash benefits generally increase with increasing cycle length. There are several possible explanations for this observation. Longer cycle lengths may indicate greater traffic volumes and cross traffic, thus a greater potential for angle crashes and greater benefit from implementing RLC programs.

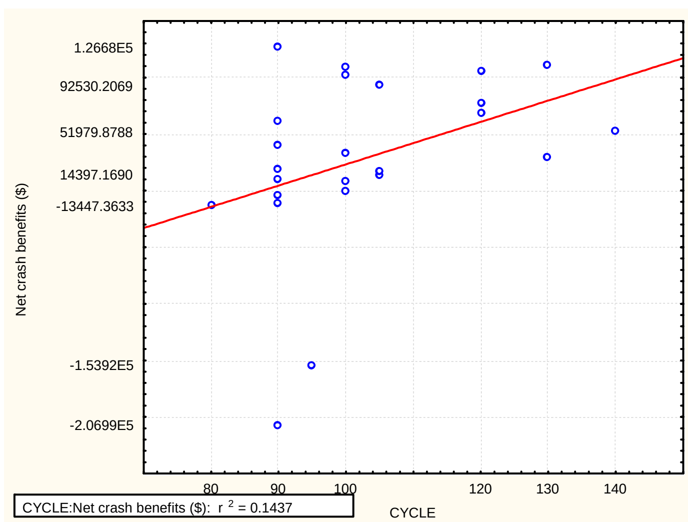

Figure 37: The net crash benefits as a function of cycle length

Figure 38 shows the effects of the length of the green phase for through movements on the net crash benefits. It indicates the net crash benefits are positively associated with the length of the green phase. Green phase and cycle length are related, of course, and so this finding is not surprising, and indicates a high volume intersection.

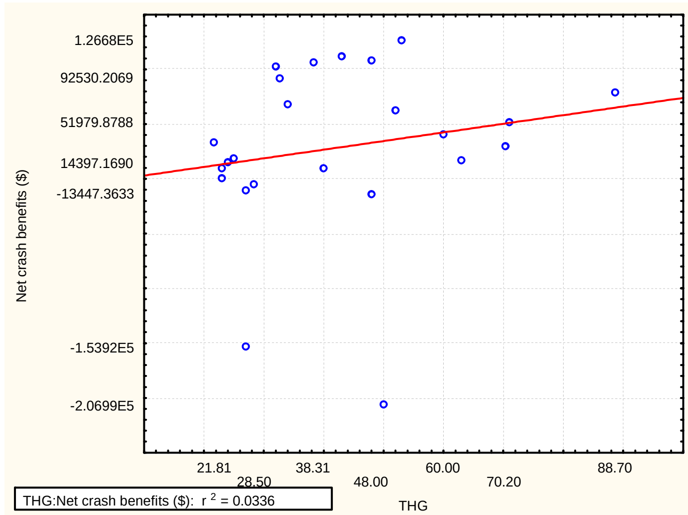

Figure 38: The net crash benefits as a function of length of green phase

Similarly, the proportion of green phase is positively associated with the net crash benefits shown in Figure 39.

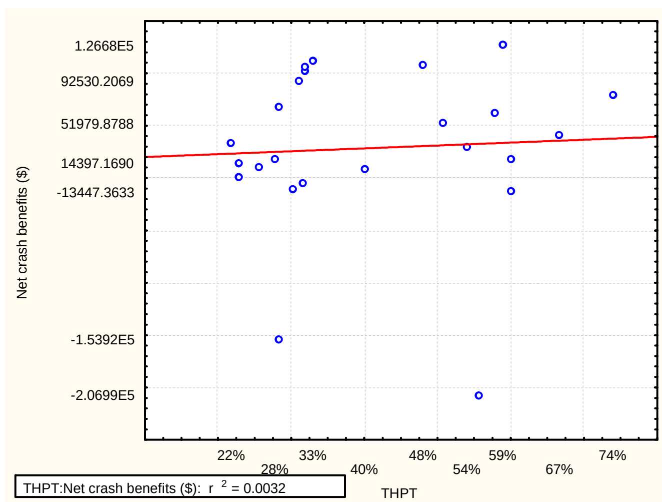

Figure 39: The net crash benefits as a function of length of portion of green phase

The relationship between approaching speeds and the net crash benefits is illustrated in Figure 40. The approaching speed (as reflected by posted speed) is positively associated with the net crash benefits, as found in previous research. This is not surprising, since high speeds are associated with higher injury severities and thus RLCs may reduce severities considerably (which are more severe on average for angle than for rear-end crashes).

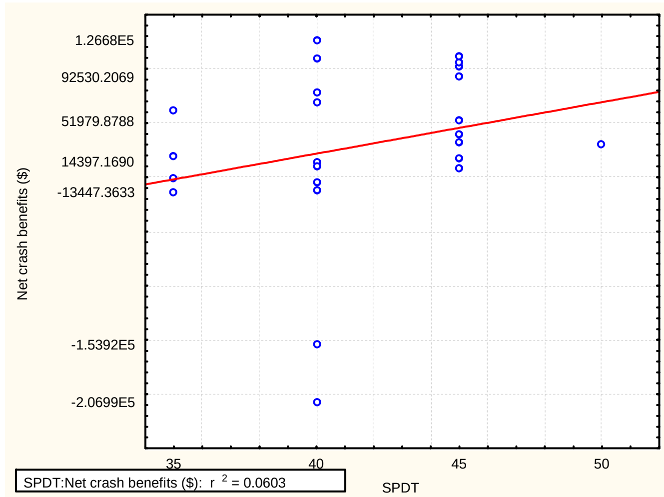

Figure 40: The net crash benefits as a function of posted speed limits

Lastly, the effects of warning signs are investigated. As mentioned, the City of Scottsdale used warning signs at two intersections (see Table 9). Table 81 shows the average crash benefits by the existence of warning signs, but the comparisons are conducted using the crash benefits of the RLCs in Scottsdale. When a warning sign is installed at an intersection, the crash benefits from angle and left-turn crashes are greater than those from intersections without a sign. In contrast, the crash costs from rear-end crashes are greater for intersections with a warning sign. In other words, drivers seem to be less likely to run a red light but more likely to rear-end a lead vehicle when they are warned that a RLC is present.

Table 81: The average crash benefits/costs by the existence of warning signs in Scottsdale

	Angle and Left-turn crashes	Rear-end Crashes
With Signs	$142,562	-$55,230
Without Signs	$46,418	-$3,962

Nevertheless, the benefits of RLCs are likely to increase with warning signs because the crash benefits from angle and left-turn crashes for intersections with a warning sign are significantly greater than those for intersections without a warning sign. In addition, the result should be viewed as preliminary since only 2 out of 14 intersections had warning signs and so it is quite possible that other unobserved factors accounted for the observed differences.

In sum, these (tenuous) relationships suggest that the net crash benefits are likely to be larger when the possibility of red light running increases. Theoretically, these variables (i.e., approach speeds, length of cycle, length of green phase, and portion of green phase) are positively related with the number of red light running crashes and benefits. These cursory findings are consistent with recent work by Bonneson and Zimmerman (2004a), where a regression model for predicting red light running frequencies (based on 275 observations) shows similar relationships. Again it should be noted, however, that statistically significant results could not be obtained due to sample sizes in this current study.

The differences in aggregate effects between jurisdictions

In this section, the effects of RLCs in two jurisdictions are statistically compared. In addition, the differences are explained and discussed.

Are safety effects different between jurisdictions?

The benefits of the RLC programs have been described in previous sections. It was shown that the City of Scottsdale's RLC program, as a whole, is performing better than the City of Phoenix's with respect to overall net crash benefits. However, the confidence intervals for the crash benefits are quite large, and in fact suggest that the mean estimated benefits may not be all that different. It was then shown that the best performing intersections, in terms in expected benefits, are similar in the two cities.

This section seeks to answer whether the two jurisdictions are significantly different from each other, and if so, in what ways. In other words, there are differences beyond overall net crash benefits, such as rear-end crashes, angle crashes, and so on, that may or not be different between the two jurisdictions and their programs. In addition, the variability in performance of intersections is of interest.

The comparisons between jurisdictions are performed in terms of both the net crash benefits and the indices of effectiveness. The comparison of the net crash benefits is used to test whether economic effects are the same across the jurisdictions. However, since the angle and left-turn crashes are combined in the net crash benefits, the comparison of indices of effectiveness (i.e., θ) is performed to test whether the effects on angle and left-turn crashes are the same respectively.

Independent *T* tests (parametric) and Wilcoxon rank sum tests (nonparametric) are simultaneously conducted to compare the measurements across the two jurisdictions. Under the normality assumption, the *T* tests are conducted (H_0: $\mu_p = \mu_s$; H_1: $\mu_p \neq \mu_s$). Here, μ_p is the mean measurement (i.e., the mean of the crash benefits and index of effectiveness) in Phoenix and μ_s is the mean measurement in Scottsdale. In addition, *F* tests are conducted in order to test whether the unknown variances for two jurisdictions are the same. Thus, the null hypotheses for F test are "H_0: $\sigma^2_p = \sigma^2_s$; H_1:~ H_0". Again, σ^2_p and σ^2_s are the variances of each measurement in each jurisdiction. As a result, if the null hypothesis of F test (i.e., comparing two variances) is not rejected, the pooled *T* tests are conducted. Otherwise, the *T* tests with unequal variances are conducted. If the sample sizes are reasonably large, the *T* tests are quite robust with respect to non-normality.

However, for small samples, and particularly when the variances are unequal, the *T* may lead to invalid conclusions. Alternatively, the Wilcoxon rank sum test (equivalently, the Mann-Whitney U test) is used. The null and alternative hypotheses for test are "H_0: The two jurisdiction distributions are drawn from the same population; H_1: reject H_0". In this test, the U statistic is used. It is a measure of the difference between the ranks of two samples. Based on the assumption that only location (mean or median) differences exist between two populations, a large or small value of the test statistic provides evidence of a difference in the location of the two populations. For large samples the distribution of the U statistic is approximated by the normal distribution. The convergence to the normal distribution is rapid, such that for $n_1 \geq 10$ and $n_2 \geq 10$ (Washington *et al*, 2003).

Table 82 shows the summary statistics of seven measurements of effectiveness by the jurisdictions and Figures 41 and 42 illustrate the box plots for different measurement types. As mentioned previously, the box plot shows the largest observation, the upper quartile, the median, the lower quartile, and the smallest observation. All measurements used in the comparisons are from the results of comparison correction (Phoenix) and empirical Bayes' correction (Scottsdale) on target approaches. Note that the mean values in Table 82 are different than the unbiased composite effects (θ) calculated by each correction method because the mean values in Table 82 are simply an arithmetic average of all effects, not unbiased estimates for composite effects (see step 3 in Table 36).

Table 82: Summary statistics for measurement of effectiveness: crash benefits and θ

Measurement type	Crash type	Jurisdictions	Mean	Median	Std. dev
Crash benefits	Angle and Left-turn crashes	Scottsdale	60152.48	53022.08	51054.58
		Phoenix	32990.33	42550.05	81008.48
	Rear-end crashes	Scottsdale	-11285.8	-4549.00	22990.60
		Phoenix	-32539.9	-24804.60	65634.10
	Total crashes	Scottsdale	48866.72	42471.52	44344.0
		Phoenix	450.42	16400.87	105630.8
Index of effectiveness (θ)	Angle crashes	Scottsdale	1.181	0.860	0.848
		Phoenix	0.482	0.435	0.368
	Left-turn crashes	Scottsdale	0.511	0.520	0.381
		Phoenix	0.882	0.834	0.296
	Rear-end crashes	Scottsdale	1.346	1.106	0.771
		Phoenix	1.566	1.554	0.734
	Total crashes	Scottsdale	0.831	0.789	0.248
		Phoenix	1.055	1.031	0.332

* N: Phoenix =10; Scottsdale=14

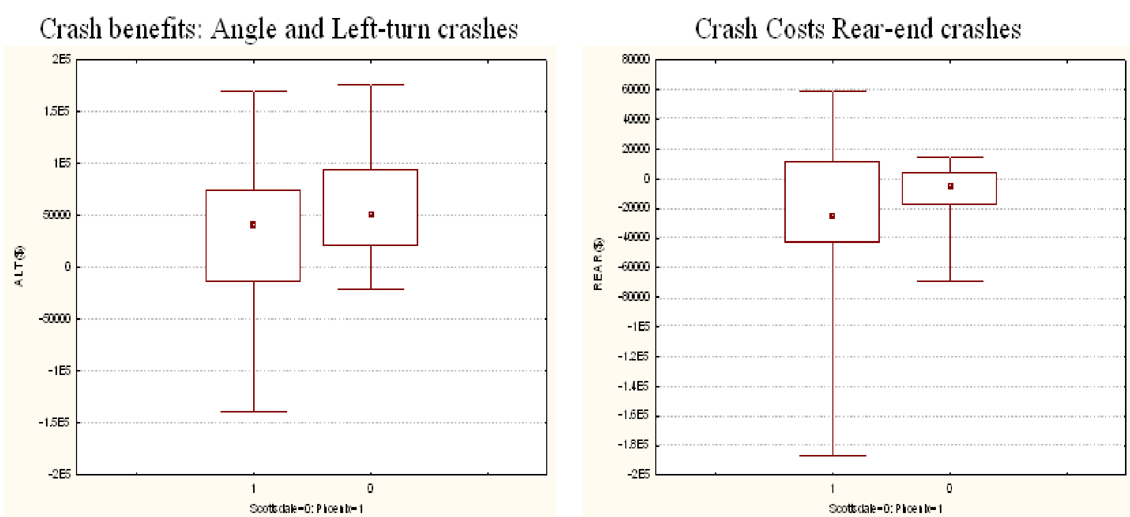

Figure 41: Box plots for the crash benefits and costs

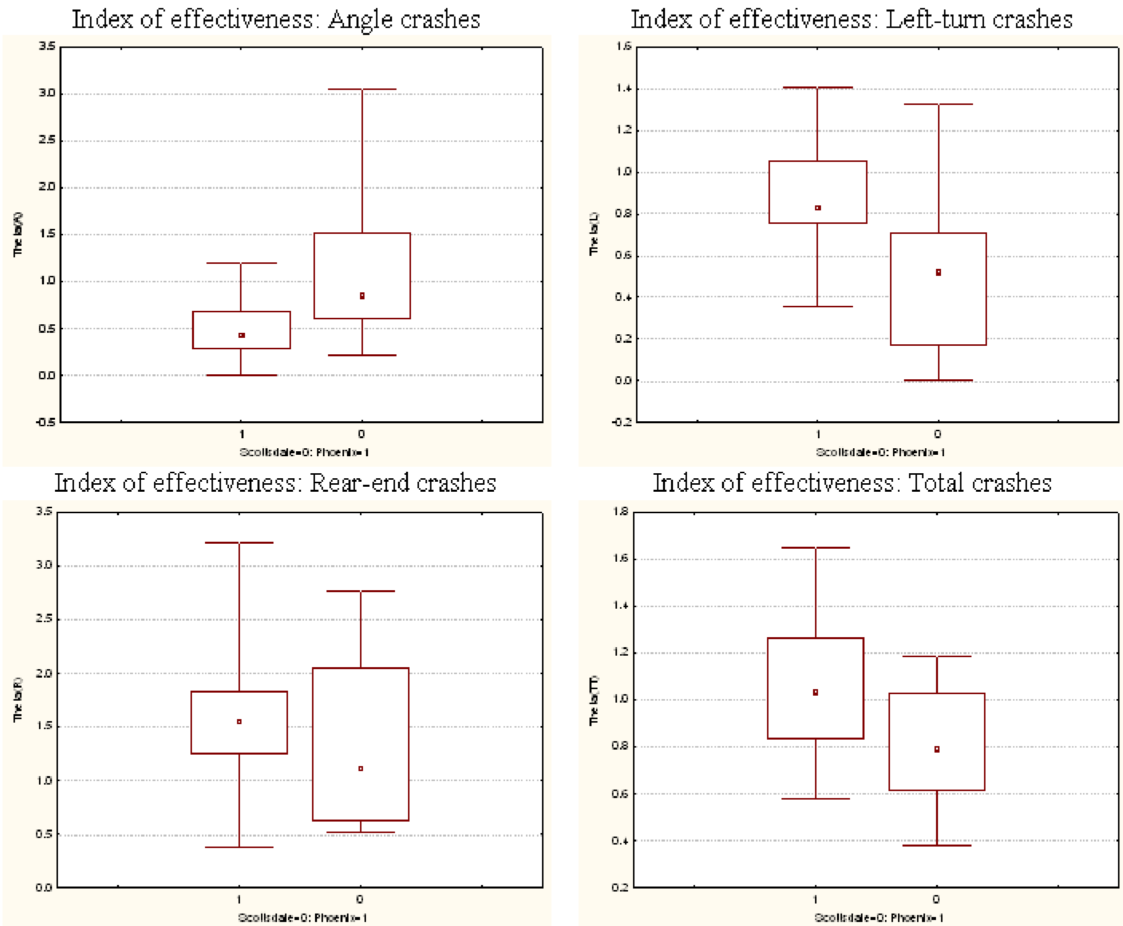

Figure 42: Box plots for the index of effectiveness

Table 83 shows the results of tests. Both parametric and nonparametric tests lead to similar results. They show that the means of θ for angle crashes and left-turn crashes are statistically different at the 5% significant level, while other measurements are similar between the two jurisdictions. That is, even though the measurements of effectiveness appear to vary from the jurisdictions, they are statistically identical except the effects on angle crashes and left-turn crashes. In addition, the one-tail tests show that the effects of RLCs on angle crashes in Phoenix are greater than those in Scottsdale (p-value=0.0065). In contrast, the effects of RLCs on left-turn crashes in Phoenix are less than those in Scottsdale (p-value=0.0087). However, even though there are differences between the effects on two crash types, the combined effects denoted as the crash benefits for angle and left-turn crashes are similar at a 5% significant level.

Table 83: The results of T test and wilcoxon rank sum tests

Variable		t-test		Wilcoxon rank sum test		
		t	p-value	U	Z	p-value
Net crash benefits	Angle and LT	-1.00929	0.323807	57	-0.761202	0.446537
	Rear-end	-0.98191*	0.348044	54	-0.936864	0.348829
	Total	-1.36601*	0.198540	55	-0.878310	0.379776
Index of effectiveness	*Theta (A)*	*-2.74565**	*0.012916*	*30*	*-2.34216*	*0.019173*
	Theta (L)	*2.57061*	*0.017443*	*27*	*2.517822*	*0.011809*
	Theta (R)	0.70122	0.490519	58	0.702648	0.482276
	Theta (T)	1.893748	0.071483	42	1.639512	0.101108

* t value is calculated under the unequal variance assumption

In summary, the results show that there are no statistical differences between the crash benefits across the jurisdictions. However, the effects on angle crashes and left-turn crashes are statistically different across the jurisdictions. Moreover, the results of the one-tail tests show that the effects on angle crashes in Phoenix are significantly greater than those in Scottsdale, while the effects on left-turn crashes in Phoenix are less than those in Scottsdale. In the next subsection, these differences are explained.

What factors explain differences between jurisdictions?

There are no statistically significant differences between the crash benefits between the jurisdictions, as discussed previously. Statistically significant differences between the jurisdictions are the effects of RLCs on angle and left-turn crashes.

Table 84 shows the differences in these effects (unbiased estimates). Again, the estimates shown in Table 84 are from the results of comparison correction (Phoenix) and empirical Bayes' correction (Scottsdale) at target approaches. Figure 43 shows the 95% CIs around these estimates.

The cross tabulation (i.e., Table 84) shows that the distributions of the effects on two crash types are different between the jurisdictions. Thus, it is necessary to investigate what factors may contribute to these differences. In order to examine the factors, the independent *T* test and Wilcoxon Rank Sum test are conducted again. Using these tests it is investigated whether the means or medians of various factors (e.g., length of cycle) are significantly different between the two jurisdictions.

Table 84: The index of effectiveness (unbiased estimates) between the jurisdictions

Jurisdictions	Angle Crashes	Left-turn Crashes
Phoenix	42%	10%
Scottsdale	20%	45%

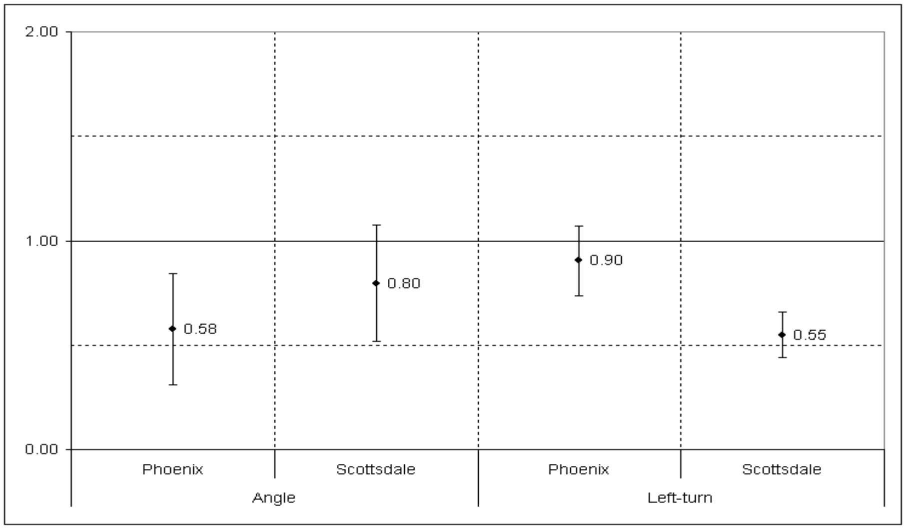

Figure 43: 95% CIs for index of effectiveness of angle and left-turn crashes

Table 85 shows the results of these statistical tests (statistically significant tests are shown initalic type). The tests reveal that the length of cycle, the yellow interval time for through movements on target approach, and posted speed limits on target approaches are statistically different between the jurisdictions at a 5% significance level. In addition, one tailed tests show that the means or medians of these three variables in Scottsdale are greater than those in Phoenix. Table 86 shows the descriptive statistics for these variables in both jurisdictions. While an observed statistically significant difference between these variables between jurisdictions does not assign causation to these factors, it does identify these factors as possible or plausible factors in contributing to differences in RLC performance between the two jurisdictions.

Table 85: The results of hypothesis tests by parametric and non-parametric methods

Variable	t-test		Wilcoxon rank sum test		
	t	p-value	U	Z	p-value
Cycle	*-3.03**	*0.01*	*31.00*	*-2.28*	*0.02*
THG	-0.81	0.43	60.00	-0.59	0.56
THY	*-3.81*	*0.00*	*13.50*	*-3.31*	*0.00*
THPT	0.17	0.86	67.00	-0.18	0.86
THL	0.30	0.77	67.00	0.18	0.86
LTL	-1.99*	0.06	46.50	-1.38	0.17
SPT	*-2.90*	*0.01*	*28.50*	*-2.43*	*0.02*
SPC	-0.88	0.41	44.50	-1.49	0.14

* t value is calculated under the unequal variance assumption

Table 86: Summary statistics of significantly different variables between jurisdictions

Variables	Jurisdictions	Mean	Median	Std. dev
Cycle length	Scottsdale	109.29	105.00	17.63
	Phoenix	94.00	90.00	5.68
Length of yellow time for through movements	Scottsdale	4.41	4.40	0.47
	Phoenix	3.78	3.80	0.27
Posted speed limits	Scottsdale	43.21	45.00	3.72
	Phoenix	39.00	40.00	3.16

* N: Phoenix =10; Scottsdale=14

Figures 44 through 46 show the relationships between these variables and indices of effectiveness for various crash types. In all relationships, the effects on angle crashes decrease as the magnitudes of these variables increase, while the effects on left-turn crashes increase with increases in these variables. Note that a small θ indicates high effects. For example, the index of effectiveness for angle crashes increases as the cycle length increases, but the θ for left-turn crashes decreases with increasing cycle length.

As a result, if the values of these variables are relatively high, it is likely that the effects on angle crashes are relatively small, but the effects on left-turn crashes are high (and vice versa). The unbiased estimates in Table 84 reflect these relationships. The cycle lengths, speed limits, and yellow interval times in Scottsdale are significantly greater than those in Phoenix. Thus, the effects on left-turn crashes in Phoenix (10%) are less than those in Scottsdale (45%), while the effects on angle crashes in Phoenix (42%) are greater than those in Scottsdale (20%).

These observations are not entirely intuitive, and require some explanation (*post-hoc*). It appears that RLCs are not as effective with regard to angle crashes (through movement crashes from drivers running red lights) when cycle lengths, yellow intervals, and speed limits increase. Driving speeds influence cycle lengths and yellow intervals, with higher driving speeds requiring longer intervals. Thus, these variables are highly correlated, and may capture the same general effect. If one focuses on speed, we see that higher speeds are associated with greater numbers of angle crashes (through movement vehicles colliding with cross traffic vehicles). It is very possible that cross traffic vehicle drivers are less likely to see and avoid entering vehicles when they are entering at high speeds (compared to lower speeds). Also, it is possible that higher speed vehicles believe they will enter an intersection prior to a red indication and avoid a red light running violation compared to lower speed approaches. Left turning vehicles, in contrast, must slow down prior to the intersection in order to negotiate a turn, and so may be more affected by the RLC systems. Although these trends appear to emerge from the data, the sample sizes are small, outliers exist, and so these trends need to be verified with further study.

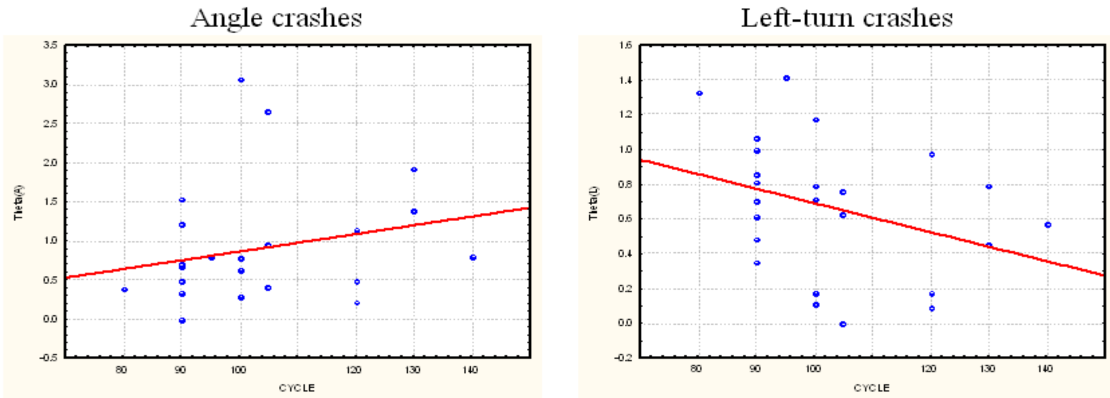

Figure 44: Index of effectiveness as a function of length of cycle

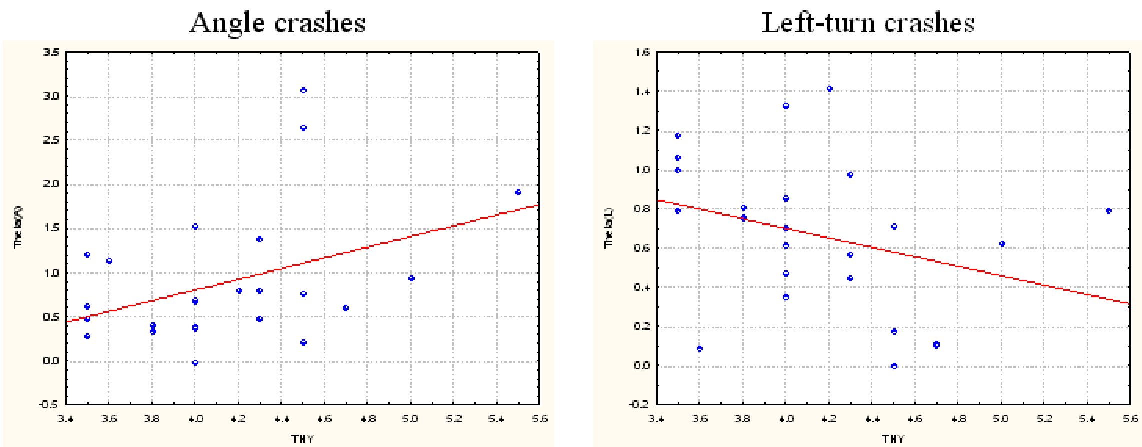

Figure 45: Index of effectiveness as a function of length of yellow time

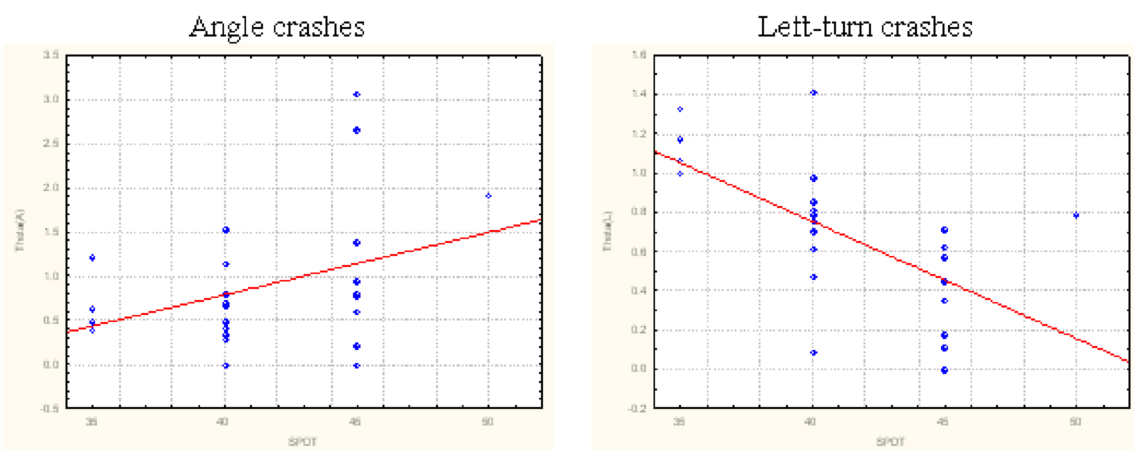

Figure 46: Index of effectiveness as a function of posted speed limits

Another difference between the jurisdictions is the left-turn control (i.e., lagging vs. leading). The left-turn control has been developed to increase the left-turn capacity and reduce delay at intersections by providing an exclusive turn phase for left turns as well as a permissive phase during which left-turns can be made as gaps in opposing through traffic will allow. These left-turn controls can precede (lead) or follow (lag) the through phase. These various left-turn control methods are summarized in Figure 47. Left-turn control can be categorized by other variables as well (e.g., actuated vs. fixed). If actuated, it may also be necessary to investigate whether the detection is of the first waiting vehicle or the third waiting vehicle. However in this study left-turn control is categorized as shown in Figure 47.

Permissive (Unprotected)	No exclusive phase for left-turning traffic which must use gaps in oncoming traffic and amber at the end of green.
Protected (Exclusive)	Exclusive phase for left turning traffic. Leading, if left-turning traffic starts with through traffic, lagging otherwise.
Protected/ Permissive (Leading)	Exclusive followed by Unprotected. Some vehicles may continue to turn left after protection has expired and conflict with the through traffic
Permissive/Protected (Lagging)	Unprotected followed by Exclusive. Left turning vehicles have fewer conflicts with through traffic. May make crossings by pedestrians easier.

Figure 47: Principal options for left-turn control [source: Hauer, 2004]

Table 87: Number of RLC intersections by left-turn control category

Jurisdictions / Left-turn controls	Phoenix	Scottsdale
Permissive (unprotected)	–	–
Protected (leading)	1	–
Protected/Permissive (leading)	9	–
Protected (lagging)	–	11
Permissive/Protected (lagging)	–	3
Total	**10**	**14**

All RLC intersections in Phoenix except one (P10: 19th Ave. & Thunderbird) are utilizing the protected/permissive left-turn control. At the one exception, exclusive protected leading left-turn control (i.e., the left-turn is not permitted during the green phase for through movements) is being utilized. A leading left-turn control is being utilized at all RLC intersections in Phoenix. In contrast, the lagging left-turn control is being utilized at all RLC intersections in Scottsdale. Protected lagging left-turn control is being utilized at all RLC intersections besides three intersections in Scottsdale (S1: 68th & Camelback; S8: Scottsdale & Mercer; S13: Pima & Pinnacle Peak). At these three locations permissive/protected left-turn control is being utilized. Table 87 shows the number of intersections by each left-turn control method.

Consequently, the major obvious operational difference between the two jurisdictions is the left-turn control method (i.e., lagging vs. leading left-turn control). Thus, it is possible for the difference in left-turn control to cause the different effects on each crash types. Because these differences in control are confounded with other differences, i.e., approach speeds, cycle lengths, etc., it is extremely difficult to isolate the effects and assign causation. However, plausible explanations for the differences are provided in the following discussion.

Suppose the target approach is eastbound on a lagging left-turn control (e.g. Scottsdale). In the before period (before the RLC), the red light running related left-turn crashes on the target approach are likely to occur between two vehicles: "the last vehicle on the target approach arriving at the end of the through green phase (e.g., EB through traffic)" vs. "the first vehicle waiting for the left-turn green arrow (e.g., WB left-turn traffic)". In this case, if a left-turn crash occurs right after the start of the green arrow, it is attributable to the red light running (RLR) of a through vehicle. In addition, if a left-turn crash occurs during all red or yellow clearance time, it is attributable to the disregard of traffic signals by both involved vehicles. In contrast, the RLR related angle crashes on the target approach are likely to occur between two vehicles: "the last vehicle on the target approach arriving at the end of the through green phase (e.g., EB through traffic)" vs. "the first vehicle on crossing approach waiting for the green phase or green arrow (e.g., NB through traffic or NB left-turn traffic)". In comparison, an angle crash on a lagging left-turn control would occur when the lagging left-turn signal is skipped due to no detection of left-turning vehicles. Similarly, if an angle crash occurs after the start of the green phase or green arrow for the NB direction, it is attributable to the RLR of through traffic on the target approach.

In the after period (after RLCs), both the angle and left-turn crashes on the target approach are likely to be reduced since the RLCs might contribute to reducing the RLR of through traffic on the target approach. The results of this study shown in Table 84 also represent the reduction in frequencies of these two crash types. However, the reductions in left-turn crashes are likely to be greater than those of angle crashes because the possibilities of the conflicts of left-turn crashes are intrinsically larger than those of the conflicts of angle crashes in the lagging left-turn control condition. In other words, the reduction in RLR by RLCs is likely to be from the RLR drivers involved in left-turn crashes rather than angle crashes. The results in Table 84 support this plausible explanation: the effects of RLCs on left-turn crashes (45%) are greater than those on angle crashes (20%) in Scottsdale.

In the leading left-turn control (e.g., in Phoenix) condition, suppose the target approach is again east bound. In the before period the RLR related angle crashes on the target approach are likely to occur between two vehicles: "the last vehicle on the target approach arriving at the end of the through green phase (e.g., EB through movement)" vs. "the first vehicle on crossing approach waiting for the green phase or green arrow (e.g., NB through movement or NB left-turn movement)". Like the angle crashes in Scottsdale, if an angle crash occurs right after the start of the green phase or green arrow for NB direction, it is attributable to the RLR of through traffic on the target approach. Unlike the angle crashes in Scottsdale, however, the possibility of angle crashes in Phoenix (i.e., the leading left-turn control) exists during each cycle. On the other hand, the RLR related left-turn crashes on the target approach are likely to occur between two vehicles: "the last vehicle on the target approach arriving at the end of through green phase (e.g., EB through traffic)" vs. "the vehicle on opposing approach waiting for the gap to turn left at the end of through green phase (e.g., WB left-turn traffic)". In the after period, the angle and left-turn crashes on the target approach are likely to decrease due to the reduction in the RLR of through movements on the target approach. Unlike the lagging left-turn condition, however, the reductions in angle crashes are likely to be greater than for left-turn crashes. Of course, it is possible that the left-turn crashes could be reduced by the RLCs, but the protected/permissive leading left-turn control is likely to indicate relatively small left-turn movements. In other words, it is likely that the number of conflicts of RLR related left-turn crashes are relatively small. As a result, the reduction in RLR by RLCs is likely to be from the RLR involved in angle crashes. Again, the results in Table 84 support this plausible explanation: the effects on angle crashes (42%) are greater than those on left-turn crashes (10%) in Phoenix.

In summary, there is no statistical evidence that the economic benefits of RLCs are different between the jurisdictions. In contrast, the safety effects of RLCs on angle crashes and left-turn crashes are statistically significant. The difference in the effects on the two crash types between the jurisdictions may be explained by the difference in speed, cycle length, yellow interval time, and left-turn control across the jurisdictions. However, it is not possible to identify which of these factors is most responsible for explaining the observed differences in crash types from a statistical perspective. From a logical and engineering perspective, however, it seems likely that the combination of relatively high approach speeds and the lagging left-turn phasing in Scottsdale has led to the observed differences in RLC performance and the observed differences in estimated mean benefits of the RLC programs.

Summary of Evaluation Results

In this section, the evaluation results are summarized. It includes the results of the change in safety, indexes of effectiveness, and crash benefits. As mentioned, three methodologies including the EB method were applied to Scottsdale data, while two methodologies were applied to Phoenix data. The discussion of the four evaluation methods in this report makes clear that, on conceptual and theoretical grounds, the EB approach is the most defensible of the four approaches. The primary reason is because only the EB approach accounts for regression to the mean (Harwood *et al*., 2002) and because the approach involves corrections for traffic and other factors. Thus, 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 over the naïve approach).

City of Phoenix

The estimates of index of effectiveness and their standard deviations are summarized in Table 88. The results of the comparison group method suggest that angle and left-turn crashes on all approaches are reduced by 14% (100*(1-0.86)) and 1% respectively. In contrast, rear-end crashes are increased by 20% on all approaches. On target approaches, the magnitudes of reductions and increases are significantly greater than those for all approaches. The direct impacts of RLCs on target approaches are greater than the overall impacts including spillover effects. That is, even though the existence of a RLC on an intersection approach produces changes in driver behavior, the effects on the non-RLC approaches were not observed.

Table 89 shows the summary of crash benefits resulting from the comparison correction. For all approaches, the net benefit is negative, or resulted in a cost of $324,836/year. This finding suggests that the benefits from the reductions in angle/LT crashes are less than the costs from increases in rear-end crashes. On target approaches, in contrast, the net benefit is $4,504/year, indicating that the benefits from angle/LT crashes exceed the costs of additional rear-end crashes. Despite a 42% reduction in angle crashes, the net benefit is relatively small because a large proportion of the reductions in angle and left-turn crashes are PDO crashes.

Table 88: Summary of indexes of effectiveness in Phoenix: estimate (standard deviation)

Approach	Method	Angle	Left-turn	Rear-end	Total
All approaches	Simple correction	0.90 (0.15)	1.06 (0.09)	1.26 (0.13)	1.10 (0.07)
	Comparison correction	0.86 (0.12)	0.99 (0.07)	1.20 (0.10)	1.06 (0.05)
Target approaches	Simple correction	0.61 (0.16)	0.96 (0.11)	1.58 (0.24)	1.07 (0.09)
	Comparison correction	0.58 (0.13)	0.90 (0.08)	1.51 (0.17)	1.03 (0.07)

Note: the estimates less than 1 indicate a decrease in crashes.

Table 89: Net crash benefits per year in Phoenix from comparison group method

Approach	Method	Lower	Mean	Upper
All approaches	Angle and Left-turn Crashes	-$1,315,925	$12,752	$1,341,428
	Rear-end Crashes	-$1,127,492	-$337,588	$452,315
	Total	-$2,443,417	-$324,836	$1,793,744
	Maximum expected benefits	$218,474/year/intersection		
Target approaches	Angle and Left-turn Crashes	-$644,859	$329,903	$1,304,666
	Rear-end Crashes	-$903,058	-$325,399	$252,260
	Total	-$1,547,917	$4,504	$1,556,926
	Maximum expected benefits	$99,150/year/intersection		

Considering the above results, the effects of RLCs on safety in Phoenix are summarized as follows:

1) Similar to previous studies, angle and left-turn crashes are reduced and rear-end crashes increase.
2) Increases in angle/left turn and decreases in rear-end target crashes on target approaches are significantly greater than those on all approaches, indicating that spillover effects were not observed.
3) The net crash benefit is relatively small because the RLCs in Phoenix contribute more to reducing angle and left-turn PDO crashes than to reducing fatalities and injuries associated with these crashes.

City of Scottsdale

The estimates of indexes of effectiveness and their standard deviations are summarized in Table 90. Angle and left-turn crashes on all approaches decreased by 17% and 40% respectively, while rear-end crashes increased by 45%. On target approaches the magnitudes of reductions in angle and left-turn crashes are slightly greater than those for all approaches. Again, the finding suggests that the direct impacts of RLCs on target approaches are greater than the spillover effects to other approaches. In contrast the increase in rear-end crashes on target approaches is less than that for all approaches, indicating that the spillover effects for rear-end crashes are higher than the direct effects. This result is counterintuitive and requires further investigation to explain. Total crashes on all approaches increased by 6%, while those on target approaches are reduced by 11%.

Table 90: Summary of indexes of effectiveness in Scottsdale: estimate (standard deviation)

Approach	Method	Angle	Left-turn	Rear-end	Total
All approaches	Simple correction	0.69 (0.09)	0.59 (0.06)	1.48 (0.10)	1.03 (0.05)
	Traffic flow correction	0.70 (0.09)	0.59 (0.06)	1.62 (0.13)	1.07 (0.06)
	EB correction	0.83 (0.08)	0.60 (0.05)	1.45 (0.06)	1.06 (0.04)
Target approaches	Simple correction	0.80 (0.14)	0.52 (0.06)	1.57 (0.18)	0.89 (0.07)
	Traffic flow correction	0.83 (0.15)	0.52 (0.06)	1.67 (0.22)	0.91 (0.07)
	EB correction	0.80 (0.14)	0.55 (0.06)	1.41 (0.11)	0.89 (0.05)

Table 91: Crash benefits per year in Scottsdale from EB correction

Approach	Method	Lower	Mean	Upper
All approaches	Angle and Left-turn Crashes	$333,214	$1,249,336	$2,165,458
	Rear-end Crashes	-$1,294,993	-$412,875	$469,242
	Total	-$961,779	$836,460	$2,634,700
	Maximum expected benefits	$197,624/year/intersection		
Target approaches	Angle and Left-turn Crashes	-$372,941	$842,135	$2,057,210
	Rear-end Crashes	-$662,606	-$158,001	$346,604
	Total	-$1,035,547	$684,134	$2,403,815
	Maximum expected benefits	$106,765/year/intersection		

On all approaches, the net benefit is $836,460 per year, even though total crashes increased by 6%. The net benefit derives from the reduction in severe injuries from angle/LT crashes exceeding the costs from the increases in rear-end crashes. On target approaches the net benefit is $684,134 per year. The magnitude of the net benefit on target approaches is more than that for all approaches (on a per approach basis). For example, if the net benefit on all approaches is distributed to each approach at a 4-leg intersection under the assumption that the RLC affects safety evenly across approaches, the net benefit allocated to each approach would be $209,115 ($836,460/4).

From the above results, the effects of RLCs on safety in Scottsdale are summarized as follows:

1) Similar to previous studies and results for Phoenix, angle and left-turn crashes are reduced and rear-end crashes increase.
2) The magnitudes of reduction or increase for each crash type on target approaches are slightly greater than those on all approaches, indicating the spillover effects are present, but relatively smaller than the effect on target approaches.
3) The crash net benefit is relatively large because the RLCs in Scottsdale contribute more to reducing the costs of fatality and injury crashes associated with angle and left-turn crashes than to increasing the costs associated with PDO rear end crashes.

IV. CONCLUSIONS AND RECOMMENDATIONS

The following conclusions and recommendations are derived from the various aggregate and disaggregate analyses that have been conducted as part of this study and that are discussed in detail in the body of this report. Aggregate analyses refer to the analysis of a set of RLC intersections acting together—the 10 intersections in Phoenix as a "system" or "program" of intersections, and the 14 intersections in Scottsdale. Disaggregate analyses, in contrast, have examined individual RLC intersections irrespective of in which jurisdiction they reside. It should be noted that similar to other studies on this subject, relatively small sample sizes coupled with natural variability and confounding of factors contributing to motor vehicle crashes have led to many statistically insignificant conclusions. It is only through agreement with past study results, the analysis of trends, the analysis of expected effects, and agreement with engineering expectations (engineering plausibility) that conclusions are derived. The conclusions, however, would benefit from further study on RLC effectiveness with greater numbers of intersections, crashes, and RLC program features. The conclusions are broken down by *City of Phoenix*, *City of Scottsdale*, and *General* and are followed by study recommendations.

City of Phoenix Aggregate Conclusions

The effects of red light cameras are assessed at 10 intersections in Phoenix equipped with RLCs. The final results are based on the comparison group method results, which is the best method available for the Phoenix data. The results for target approaches are:

- Angle crashes decreased by 42%
- Left-turn crashes decreased by 10%
- Rear-end crashes increased by 51%
- The estimated net crash benefit is $4,504/year for the 10 target approaches

The estimated impacts on all approaches are less than those on target approaches. The results for all approaches (including both RLC and non-RLC approaches at RLC intersections) are:

- Angle crashes decreased by 14%
- Left-turn crashes decreased by 1%
- Rear-end crashes increased by 20%
- The estimated net crash benefit is - $324,836/year (i.e., negative, meaning more costs than benefits) for the 10 intersection approaches

Spillover effects do not appear to be present. The net crash benefit on the targeted approaches is relatively small because the RLCs in Phoenix contribute more to reducing angle and left-turn PDO crashes than to reducing fatalities and injuries associated with these crashes. In addition, a few intersections dis-benefited significantly from the installation of RLCs and these intersections heavily weighted the "average" benefit for the 10 RLC intersections.

City of Scottsdale Aggregate Conclusions

The safety effects of red light cameras are assessed at 14 intersections in Scottsdale, and the final results are based on the before-and-after study with empirical Bayesian correction for regression to the mean. The impacts on target approaches are as follows:

- Angle crashes decreased by 20%
- Left-turn crashes decreased by 45%
- Rear-end crashes increased by 41%
- The estimated net crash benefit is $684,134/year on the 14 target approaches

The safety impacts on all approaches are slightly less than those on target approaches except for the case of rear-end crashes:

- Angle crashes decreased by 17%
- Left-turn crashes decreased by 40%
- Rear-end crashes increased by 45%
- The estimated net crash benefit is $836,460/year for the 14 intersection approaches

Spillover effects are present and slightly less than the effects on target approaches. The crash net benefit is relatively large because the RLCs in Scottsdale contribute more to reducing the costs of fatality and injury crashes associated with angle and left-turn crashes than to increasing the costs associated with PDO rear end crashes.

General Conclusions

- 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 that this is an important consideration in the adoption and/or implementation of such programs.
- RLCs appear to systematically 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 braking suddenly to avoid a possible violation and fine.
- The RLCs in Phoenix and Scottsdale are effective on target approaches, but the magnitude of effectiveness in Scottsdale appears to be greater than in Phoenix. However, they are statistically similar—that is, the statistical variability surrounding the estimated benefits for the two cities is large. Crash severity is affected by RLCs, and the extent to which severity is reduced for angle and left-turn crashes determines whether the RLC program yields a net positive benefit. Increases in rear-end crashes as a result of RLCs tend to yield increases in property damage only crashes, and thus do not significantly impact the economic analysis.
- Analysis of individual intersections, albeit with low precision, suggests that RLC equipped intersections in Phoenix and Scottsdale perform similarly. That is, the "best" intersections perform similarly in the two jurisdictions and have similar expected net benefits. In fact, the top three intersections in the two jurisdictions perform similarly. This finding suggests that variability within jurisdictions is significant (e.g. larger than variability in performance between jurisdictions), and that some intersections benefit greatly from RLCs while others do not.
- Analysis of differences across intersections and jurisdictions shed some preliminary insights into RLC effectiveness at individual intersections. Observed general trends, some statistical results from this research, and engineering logic suggest that high approach

speeds and left-turn phasing are important considerations when installating RLCs. High approach speeds lead to more severe crashes, and when reduced by RLCs, lead to more significant benefits of the RLC program. Lagging left-turn phasing seems to be more significantly impacted by RLCs with respect to left-turn crashes, which tend to be relatively severe. When RLCs are installed at intersections with leading left-turn phasing, in contrast, angle crashes tend to be reduced more significantly (compared to left-turn crashes).

- It appears that the presence of warning signs benefits a RLC program. Warning signs seem to warn drivers of an upcoming RLC approach and thus drivers are more likely to avoid running a red light and get involved in subsequent angle or left-turning accidents—both of which lead to greater net benefits of the RLC program.

Recommendations

The following actions are recommended to maximize the impacts of RLCs and to address red light running and related crashes. In general, the RLC is not a panacea to address red light running problems. However, the RLC may be a promising countermeasure given the following considerations.

- It is necessary to examine whether an 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.
- Given that the conditions above are satisfied, candidate sites with high approach speeds are more likely to benefit than sites with relatively lower approach speeds, particularly for left turn crashes.
- The severity of left-turn and angle crashes at candidate sites should be examined. Left-turn related crashes are more likely to be reduced (as a result of RLCs) in the lagging phase condition, whereas angle crashes are more likely to be reduced in the leading left-turn phase condition.
- Engineering countermeasures (excluding RLCs) may be considered to deal with red light running problems (see Table 1) at candidate sites. It may be prudent to exhaust simpler and/or less costly engineering countermeasures to combat a red light running problem prior to adopting a RLC program, particular when some of the previous "ideal" conditions do not exist.
- The RLC is just one possible countermeasure that may be used to reduce red light running related crashes. Comprehensive guidance on the selection of an appropriate countermeasure is needed. The *Red-Light-Running Handbook: An Engineer's Guide to Rreducing Red-Light-Related Crashes* (Bonneson and Zimmerman, 2004b), *Guidance for Using Red Light Cameras* (FHWA/NHTSA, 2003), and *Red Light Camera Systems Operational Guidelines* (FHWA/NHTSA, 2005) are useful resources for jurisdictions wishing to examine current knowledge on alternative countermeasures.
- Further study is needed to improve sample sizes, increase the number of crashes obtained in the sample (through increased RLC intersections or longer histories), and sort out some of the confounding variables analyzed in thus study.

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Appendix: Survey Questionnaire

<u>Section I. General RLC/Automated Enforcement Program description:</u>

1. Approximately how many (total) signalized intersections are there in your jurisdiction?

2. Please indicate the month and year when automated enforcement/red light running was installed at signalized intersections in your jurisdiction.

e.g. <u>Date</u>	*<u>Intersections converted to automated enforcement/red light camera</u>*
6/2002	*1) 5th and Main, 2) 5th and Sweetwater*
8/2002	*3) Airport Blvd and Cross*

<u>Date</u>	<u>Intersections converted to automated enforcement/red light camera</u>

3. How many signalized intersections in your jurisdiction (besides the automated enforcement intersections noted in 2 above) have cameras or dummy cameras installed?

4. What is the typical camera configuration for your automated enforcement/red light running intersections?
   e.g. (front and rear cameras at 4 approaches)

5. If cameras are rotated in your jurisdiction, what is the typical camera rotation period?
   e.g. Ten cameras are currently rotated randomly to 18 locations; Four cameras to seven intersections based on analysis of violations; etc.

6. What is the "standard" definition for a red light running (RLR) violation in your jurisdiction (i.e. lag/grace time, minimum speed, point of infraction, posted speed limit)
   e.g. Curb line extended and 0.1 second delay; Curb line and no delay with 18mph over posted speed limit (35mph) minimum; Curb line and 0.1 second delay and 15 mph over posted speed limit (30 mph) minimum; 0.3 seconds into the red, 15 mph over speed limit minimum (40mph); etc.

7. Is the RLR definition constant across all enforced intersections? Yes No
   (If not, please describe differences)

8. A RLR citation is issued to the: driver vehicle owner

9. What is the standard RLR violation fine including court costs?
   e.g. $160 or $100 plus traffic school; $271, but reduced if attend traffic school; $75 -$100 plus $20 court cost if go to court, etc.

10. If the driver is ticketed, are driver points added to his/her driving record? Yes No

11. How were intersections selected to receive automated enforcement/RLC?
    e.g., High Accident Locations; Engineering judgment; Convenience; History of red-running behavior; Suggestions from police and public followed by analysis; Citation history; etc.
12. Has your agency completed any evaluations of your RLCs?
    Yes
    No, completed by others: please list who________________________

No, but planned for near future.
No

13. If completed, can you please <u>provide a copy</u> of the results with this survey?
Yes, it will be provided.
No, because____

14. If on-going or planned, could you <u>provide contact information</u> for someone leading that effort?
Yes, it will be provided.
No, because____

15. Other relevant comments or notes regarding your RLC program?

Section II. Site Specifics

16. Can you <u>provide basic site descriptions or design drawings</u> for the sites treated?
Yes, it will be provided.
No, because____

17. Can you <u>provide a record of changes to the phasing or intersection geometrics</u> that were completed *at the same time* as the RLC installation?
e.g., yellow interval change; protected left-turn phase added; geometric changes such as widening lanes or addition of turn lanes; re-surfacing, etc.
Yes, it will be provided.
No, because____

18. Can you <u>provide a record of any changes</u> during both a 5-year period before and after RLCs systems were installed at your signalized intersections (geometrics, signage, striping, surface, etc.)?
Yes, it will be provided.
No, because____

Can you provide a <u>record of traffic counts</u> for each approach of the treated intersections?
Yes, it will be provided.
Yes, but only for a subset of treated sites, including________________________________
No, because____

18.1. If "Yes," please describe the traffic counts that are available?
e.g. 5 to 10 years; complete counts for 3 past years on all intersections including turning movement counts in 15-minute intervals; AADT and TMC for 5 years; Some tube counts; etc.

18.2. Does this data file on the treated locations contain historic data (i.e., traffic data for 5 years before the treatment and up to the present year)?
Yes
No

19. Can you <u>provide historic traffic count data available for other *signalized* intersections</u> that do not have the treatment?
Yes, it will be provided.
No, because____

20. Can you <u>provide historic traffic count data available for other *unsignalized* intersections</u> in your jurisdiction?
Yes, it will be provided.
No, because____

21. Are the traffic volume/turning movement data available in electronic format?
    Yes
    No

22. Other relevant comments or notes on specifics of RLC intersections?

Section III. Crash data:

23. Can you provide computerized crash data for all treated sites (e.g. a crash database)?
    Yes, it will be provided.
    No, because____

24. Can crashes in the database be linked easily to the specific intersection where they occurred?
    Yes
    No

25. Can crashes be linked to a specific approach covered by a RLC if necessary (e.g., rear-end crashes)? Does this have to be done manually by pulling hard copies of crashes?
    Yes, crashes can be linked (to a particular approach)
    Yes, crashes can be linked but it must be done manually
    No, crashes cannot be linked w/o extreme difficulty

26. What years of crash data are available for the treated sites?
    e.g. 5th and Main: 1995 to present; 5th and Sweetwater: none; Airport Blvd and Cross: 1992 to 2001

27. Can you provide computerized crash data for otherwise similar untreated signalized intersections in your jurisdiction?
    e.g. 10 years before and up to present for all sites; 1997-2001 for selected sites; 3 years prior to present; etc.
    Yes, it will be provided.
    No, because____

28. Are these crash data collected by law enforcement, or are some crashes self-reported by involved persons?
    Police only
    Police and Citizen reports

    28.1. If "Police and Citizen reports," what are the criteria for police vs. citizen report?

29. Please describe the crash-reporting threshold used by your police over the time period of the available crash data.
    e.g., all injury, PDO reporting varies by jurisdiction; $1000 PDO threshold; $200 damage or injury; etc.

30. Has the reporting threshold changed since the beginning of the before-data period; and if so, describe the changes?
    e.g. Changed from $500 to $750 in 1996
    Yes
    No
31. What is your opinion on how well the reporting threshold is followed by police and citizens?
    not at all *poor* *fair* *good* *excellent*

32. Can you provide "de-personalized" copies of all crash report forms generated since the program began?

Yes, it will be provided.
No, because____

33. Other relevant notes or comments on crash data:

Section IV. Signal Phasing.

34. Can you please identify which of the RLC signalized intersections is part of a "signal progression?"
Yes, the following intersections are part of a progression______________________
____
None are part of a progression
Unsure

35. Can you provide information on the yellow phase interval lengths during the before and after periods for each treated intersection?
Yes, it will be provided.
No, because____

36. Do you have a jurisdiction-wide standard policy on yellow intervals? If so, please describe.
e.g., 4 seconds jurisdiction wide; 3.5 seconds for approach speeds 35mph and less; ITE guidelines with following exceptions, etc.
No
Yes; describe____

37. Do you use all-red intervals at the RLC intersections in your jurisdiction?
No
Yes; describe____

38. Do you use all-red intervals at other (non-RLC) intersections?
No
Yes; describe____

38.1. If "yes", how can these intersections be identified?
e.g. spreadsheet; signal timing records; etc.

39. Can you provide an intersection inventory file that includes details of yellow intervals and all-red intervals for non-treated intersections?
Yes, it will be provided.
No, because____

39.1. If "yes," Are the intersection inventory files computerized?
Yes
No

39.2. Updated regularly?
Yes
No

39.3. Are historic data retained?
Yes
No

40. Other relevant comments or notes on signal phasing:

Section V. Publicity and Supplemental Enforcement Campaigns

41. Do you use any type of "warning/informational" signs at RLC intersections?
    Yes
    No

    41.1. If "yes," where are they located?
    e.g., at the treated approach, at both treated and untreated approaches, at the entrances to town, at the beginning of the corridor, etc.

42. Which best describes the general level of your publicity program if you had one: *(check one)*

    High: Major planned P.I. including such components as the FHWA program, other departments, TV spots, Billboards, etc.

    Medium: Moderate PI program with limited PI expenditures, but good coverage by news media

    Limited: limited PI program with only media coverage from interviews and/or a press conference
    None

43. When was the PI program initiated?
    e.g., 6 months before ticketing began; at the same time as ticketing, 2 years prior to cameras, etc.

44. Does your agency use signs that show number of ticketed violations?
    Yes, these are located____
    No

    Was there a supplemental police enforcement campaign at the RLC intersections in addition to normal enforcement? If yes, please describe.
    No
    Yes; please describe____

    44.1. If yes, how long did supplemental enforcement continue?

45. Was there supplemental enforcement at non-RLC sites?
    Yes
    No
    Unsure

    45.1. If yes, how long did supplemental enforcement continue?

46. Other notes or comments on publicity and enforcement campaigns: