Evaluation of the City of Scottsdale Loop 101 Photo Enforcement Demonstration Program

Draft Summary Report

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Executive Summary

This executive summary presents the *preliminary analysis results* of the fixed speed-enforcement camera demonstration program (SEP) that was implemented on Arizona State Route 101 from January 2006 through October 2006. The analysis is focused on quantifying:

- The impact of the SEP on speeding detections (76 mph or faster)
- The impact of the SEP on average speeds
- The effect of the SEP on traffic safety (motor vehicle crashes)
- The expected economic costs and benefits of the SEP
- The financial and public perception impacts of the program (appendix)

This evaluation, administered by the Arizona Department of Transportation (ADOT), utilizes data from the Arizona Department of Public Safety (crash reports), ADOT (motor vehicle crashes, traffic volumes, traffic speeds), the City of Scottsdale (traffic volumes and speeds), RedFlex (detections, traffic speeds), the Arizona Crash Outcome Data Evaluation System (crashes and crash costs), and the National Highway Safety Administration (crash costs). A *Final Report*, based on a more complete and expanded data set and containing additional analyses, will be available during the spring of 2007. Note that these preliminary results reflect an initial assessment with incomplete data and analyses—and so results are likely to change with updated data. It is anticipated, however, that the data and analyses presented here are sufficient to indicate the direction of effects and to draw general conclusions as to the effectiveness of the program.

Four time periods are referenced in this analysis.

- Before (2001 – 2005 – various periods)
- Warning (01/22/06 – 02/21/06)
- Program (02/22/06 – 10/23/06)
- After (10/24/06 – 12/03/06)

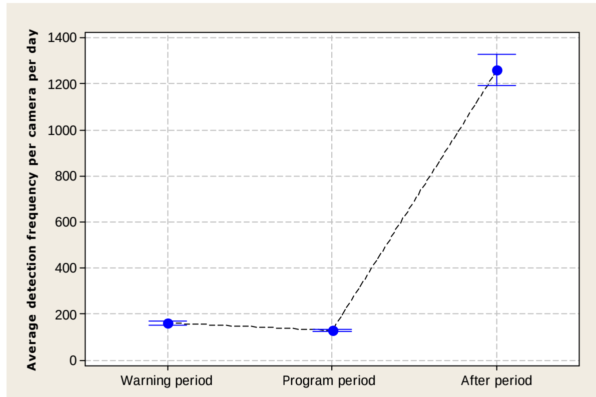
SEP Demonstration Sites

Site ID	Site	Direction
1	Scottsdale Rd. and Hayden Rd.	EB
2	Hayden Rd. and Princess Dr.	WB
3	Frank Lloyd Wright Blvd. and Raintree Dr.	SB
4	Raintree Dr. and Cactus Rd.	NB
5	Shea Blvd. and Mountain View Rd.	NB
6	Shea Blvd. and Mountain View Rd.	SB

The Scottsdale 101 automated enforcement program consists of 6 speed detection stations within a 6.5 mile segment of route 101 within the city limits of Scottsdale, Arizona. Three cameras are positioned to enforce speeds for each direction of travel (clockwise and counter-clockwise) on the Scottsdale portion of the loop 101 freeway.

Effect on Speeding Detections

The average number of speeds detected (per day per camera) in excess of 76-mph was 162.2 during the *warning* period, 129.7 during the *program* period, and 1259.7 in the *after* period. Frequencies were higher on weekends than on weekdays. The average detection frequency for weekdays significantly increased by about 825% (847% for weekends and holidays) from the *program* to *after* period.



Effect on Mean Speeds

The preliminary results reveal that mean traffic speeds were reduced by about 9.4 mph, indicating that the SEP was an effective deterrent to speeding. Reduced speeds lead to decreases in speed variation, reduced crash impact speeds, and reduced demands on vehicular control systems (braking, steering, and suspension).

Because peak hour traffic speeds are constrained by congestion, it is highly unlikely that speeds in excess of 76-mph are possible during peak periods. As a result, it is assumed that the SEP will only affect unconstrained period travel speeds (and associated crashes).

Period	Estimated Mean Speeds (mph)
Before period (1)	73.57
Program period (2)	64.17
Difference (1 – 2)	**−9.407**

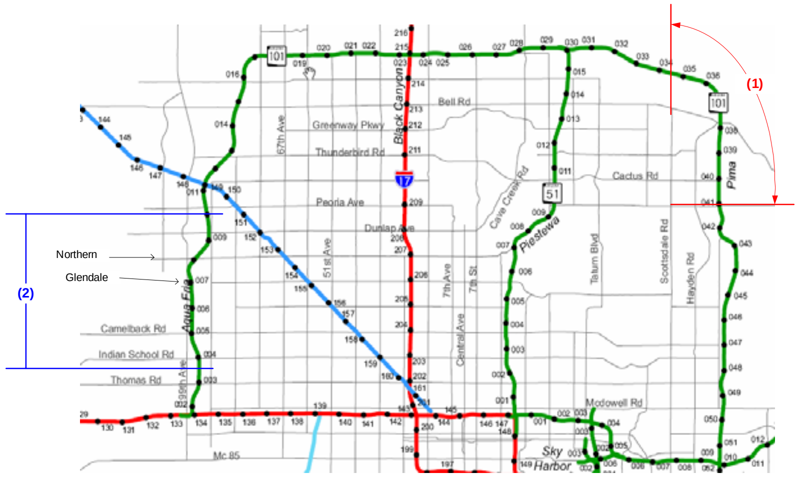
Impact on Traffic Safety

The safety analyses results are based on crash data through August 31st, 2006; however, the SEP ended on October 23rd, 2006. These additional (nearly) two months of crash data will be included in the analysis for the Final Report. Crash types affected by the SEP are categorized into four categories: single-vehicle, sideswipe-same direction, rear-end crashes, and other. These crashes constitute about 54%, 19%, 16%, and 11% of all crashes respectively. Only the off-peak periods are analyzed because of the limited expected influence of the cameras on slow moving peak period traffic.

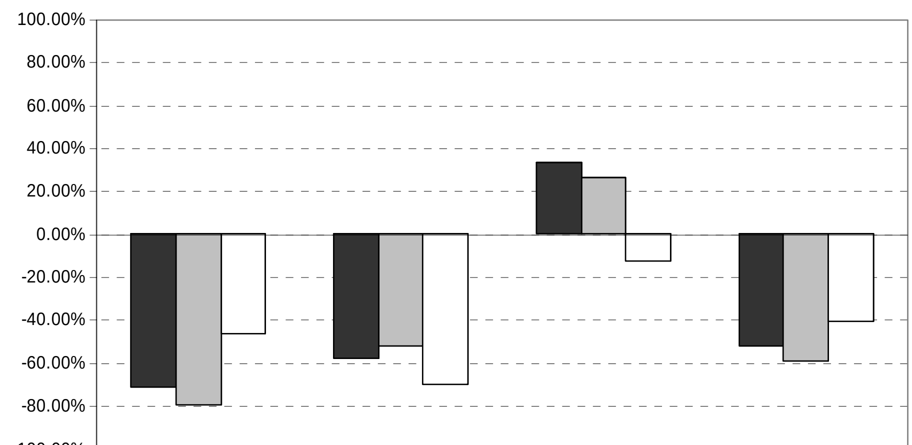
The safety analysis consists of three different methodologies: a simple or naïve before and after (BA) analysis, a BA analysis using a comparison group, and an empirical Bayes' analysis. The three analysis methods have varying assumptions, as discussed in the report. The results of the simple BA and the BA with comparison group are presented here. The comparison site is a 6.5 mile segment on the west-side 101, chosen because of the availability of traffic speed and volume data.

Comparison and Enforcement Sites

(1) Enforcement zone: MP 34.51– MP 41.06 (Approximately 6.5 miles)
(2) Comparison zone: MP 3.5 – MP 10 (6.5 miles)

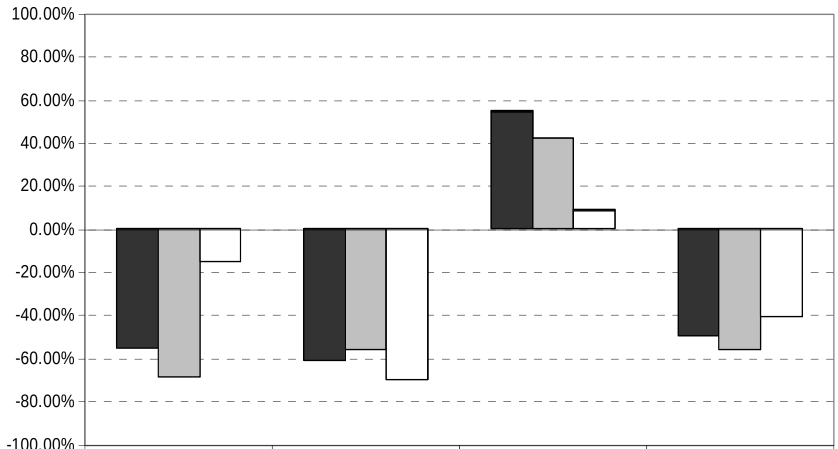


Using a BA analysis with correction for traffic flow, the estimated change in crashes from the SEP ranges from an increase of 33% (rear-end crash frequencies) to a reduction of 79% (single vehicle property damage only crashes). It should be noted that the BA approach estimates an increase in rear-end injury crashes—suggesting that rear-end crashes have increased compared to the *before* period, but a decrease (12.57%) in injuries associated with rear-end crashes. The BA approach assumes there have been no trends in crashes from the *before* to *program* periods, which is sometimes questionable due to changes in road users, weather, vehicle improvements, enforcement programs and policies, etc.



	Single Vehicle	Side-swipe (same)	Rear-end	Total
Crash Frequencies	-71.12%	-57.85%	33.24%	-51.88%
PDO Crashes	-79.44%	-52.05%	26.16%	-59.03%
Total Injuries	-46.09%	-70.26%	-12.57%	-40.34%

Using the BA analysis with the comparison site to account for crash trends on the 101, the estimated change in crashes from the SEP ranges from an increase of 55% (rear-end crash frequencies) to a reduction of 69% (single vehicle property damage only crashes). It should be noted that the comparison BA approach estimates a relatively negligible increase in rear-end injury crashes—suggesting that although rear-end crashes increase, they result in approximately the same number of injury crashes as in the before period. Nevertheless, it is not clear whether the increase in rear-end crash negates the reduction in the remaining crashes—because different crash types are associated with different crash costs. Therefore, the program effects were converted into crash costs in order to estimate the overall benefits of the SEP.



	Single Vehicle	Side-swipe (same)	Rear-end	Total
Crash Frequencies	-55.60%	-61.11%	54.51%	-49.65%
PDO Crashes	-68.69%	-56.10%	42.08%	-56.20%
Total Injuries	-14.84%	-70.00%	8.50%	-40.33%

To illustrate the economic benefits of the program, the results from both the simple BA and the BA with comparison group are presented. Annual estimated benefits of the SEP program range from 11.5 M (BA analysis with traffic correction) to $10.6 M (BA analysis with comparison group). These benefits include medical costs, other costs (lost productivity, wages, long-term care, etc.), and quality of life costs. The overall benefits appear to be very similar in magnitude across categories.

Severity	**Fatal Crashes**	**Disabling Injury**	**Evident Injury**	**Possible Injury**	**Property Damage**	**Total**
Simple BA w/r(tf)	$3,977	-$1,388	$2,382	$34	$6,546	$11,551
BA with Comparison	$5,879	-$1,905	$1,914	$206	$4,484	$10,578

Crash Benefits in $1000/year from Different Analysis Methods

Conclusions, Limitations, and Further Work

Conclusions

This preliminary study—based on the analysis of a variety of limited datasets—suggests the following:

1. Detection frequencies (speeds > 76 mph) increased by about 836% after the SEP ended. The Scottsdale 101 SEP appears to be an effective deterrent to speeding in excess of 75 mph.
2. The SEP reduced average speeds in the enforcement zone by about 9.5 mph.

3. All crashes appear to have been reduced except for rear-end crashes. Increases in rear-end crashes are traded for reductions in other crash types. Also, severity of crashes decreased within all crash types.
4. Swapping of crash types are common for safety countermeasures—many countermeasures exhibit the 'crash swapping' phenomenon observed in this study (left-turn channelization, red-light cameras, conversion of stop signs to signals, etc.).
5. Total estimated SEP benefits range from \$1.4 M to \$10.6 M per year, depending on the analysis type and associated assumptions, which suggests that the increase in rear-end crashes does not nullify the effects of the SEP on safety.
6. Estimated benefits are conservative because the Scottsdale 101 site was safer than average prior to the SEP. It is likely that benefits would increase if the SEP was applied to sites with higher than average freeways crashes.
7. Results are conservative because additional costs and benefits have not been considered: incident related congestion, reduced manual enforcement costs, risk to officers, and travel time costs.
8. It is not clear which results are more reliable, the BA with correction for traffic, the comparison group BA, or the Empirical Bayesian analysis results. At this point all three results should be weighed and considered. All three methods predict benefits, and only one predicts injury increases by a very small amount. Additional analysis should shed light on which analysis outcome is likely to be more reliable.

Limitations

The results of this analysis should be treated with caution for a variety of important reasons:

1. The results are based on small and incomplete samples. The demonstration program, which was implemented on a 6.5 section over a period of 6 months, none-the-less results in a relatively small sample of crashes. Small numbers of crashes results in large variability and uncertainty surrounding the analysis results, especially fatal and severe crashes which have high associated crash costs. In addition, approximately 7 of the 9 months of the program are evaluated in this analysis. More complete analysis will yield more reliable results.
2. Random fluctuations in crashes are commonly observed, and can influence the results significantly. In particular, severe crashes including fatal crashes will significantly influence the benefit estimates associated with the analysis.
3. Trends in crashes on the 101 are based on a small sample obtained at the comparison site. Analysis of the entire 101 set of crashes will yield more reliable estimates of crash trends on the 101 from the *before* to *program* periods. Also, comparison crashes will be used to expand the analysis (i.e. crashes during peak periods).
4. Detailed analysis of specific crashes has not been conducted as part of this analysis, and may reveal trends in crashes that have not been revealed in this analysis, such as crashes caused by drivers under the influence of drugs or alcohol, crashes as a result of preceding incidents, or crashes as a result of construction projects.

5. The entire set of costs and benefits have not been included in this analysis. The costs of reduced travel times (lost productivity of drivers) have not been included. The additional benefits of reduced risk to law enforcement personnel, of reduced incident-related congestion, and reduced 'secondary' crashes have not been included.

Planned Further Work

Since the current analyses were conducted by using incomplete data, the analysis result will be updated during the spring of 2007, and presented in the Final Report. The planned further work includes:

- Analyze priority 3 crashes (i.e., all SR 101 crashes in 2006)
- Examine additional comparison sites and comparison crashes
- Examine car-following effects
- Update databases (detections and speed)
- Increase sample size of comparison sites to improve analysis consistency
- Focus on implementation recommendations and guidelines
- Compute additional costs and benefits of program, including travel time losses, incident related congestion costs, reduced enforcement costs, and reduced officer risk.

Introduction

1.1 Background and Objectives

Speeding is recognized as one of the most important factors causing traffic crashes. In 2004, 36 percent of all motorcyclists involved in fatal crashes were speeding, approximately twice the rate for drivers of passenger cars or light trucks (National Highway Traffic Safety, 2005). Intelligent Transportation Systems (ITS) now exist to reduce speeding related crashes by enforcing speed limits with camera-based technologies. These enforcement technologies are generically called "speed cameras" and have been effective on municipal streets and arterials in Arizona (Roberts and brown-Esplain, 2005).

The City of Scottsdale began automated enforcement efforts in December of 1996. Between 1996 and 1998, four wet film mobile speed units and 6 wet film red light cameras were deployed for a total of 9 intersections on enforcement rotation, depending on the needs of the City. The cameras on city streets have helped Scottsdale improve safety (Washington and Shin, 2005). Scottsdale expanded these efforts in August of 2004 with a dual direction fixed speed enforcement system on 7700 Frank Lloyd Wright Blvd. This system covers three lanes of traffic Eastbound and three lanes of traffic Westbound on Frank Lloyd Wright Blvd. The city's recent experience on Frank Lloyd Wright Boulevard is that speed violations significantly decreased in one year period after installation of cameras.

With these experiences, the City Council on October 25, 2005, approved the nine-month *speed enforcement camera demonstration program* (hereafter SEP) on a 7.8-mile stretch of the SR 101 segment within Scottsdale. The SEP began on January 22, 2006 and ended on October 23, 2006. The demonstration program on the SR 101 freeway segment in Scottsdale is the first use of the fixed-site photo enforcement equipment on a freeway in Arizona and is believed to be the first in the nation.

Accurately estimating the impacts of the traffic safety countermeasures such as the speed enforcement cameras is challenging for several reasons. First, many safety related factors such as traffic volume, the crash reporting threshold (legal requirement to report a crash), the probability of reporting, and the driving population are uncontrolled during the periods of observation. Second, 'spillover' effects can make the selection of comparison sites difficult. Third, the sites selected for the treatment may not be selected randomly, and as a result may suffer from the regression to the mean effect. Fourth, a speed enforcement program may influence specific types of crashes—called target crashes—which often may be difficult to define and identify. Finally, crash severity needs to be considered to fully understand the safety impact of the treatment.

With these challenges in mind, this study was conducted to estimate the impact of the SEP on traffic safety, speed, and speeding behavior. More specifically, the objective of the research was to:

- Estimate the impact of the SEP on speeding behavior, which is represented as the detection frequency;
- Estimate the changes in mean speed due to the SEP;
- Estimate the impact of the SEP on traffic safety at the enforcement zone;
- Translate the impacts on crashes into estimated economic costs and/or benefits.

1.2 Description of the Demonstration Program

The cameras are at 6 fixed locations (in contrast to mobile photo enforcement vans) along the SR 101 freeway from just north of the 90th Street exit to the Scottsdale Road exit as shown in Figure 1. The directions of each site are summarized in Table 1.

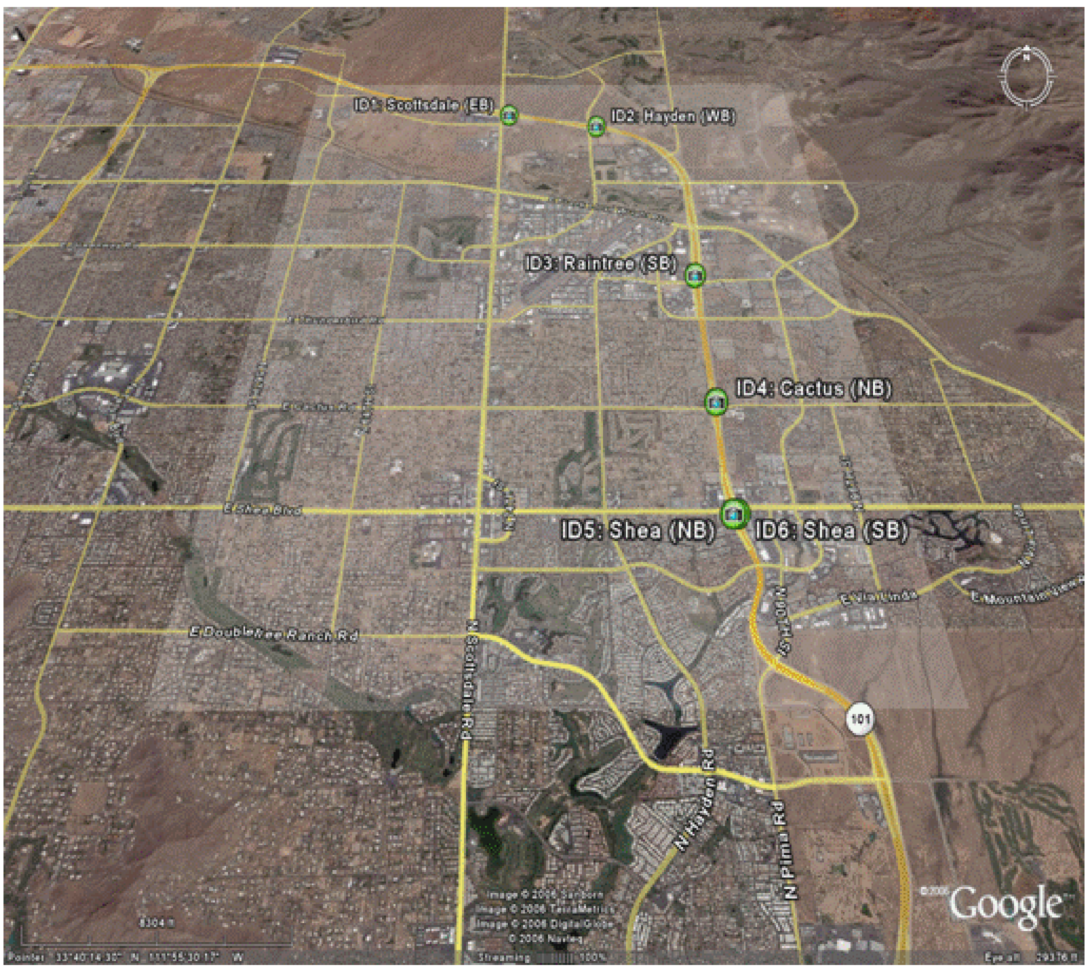


Figure 1: Location of 6 enforcement sites

Table 1: Summary of 6 demonstration sites

Site ID	Site	Direction
1	Scottsdale Rd. and Hayden Rd.	EB
2	Hayden Rd. and Princess Dr.	WB
3	Frank Lloyd Wright Blvd. and Raintree Dr.	SB
4	Raintree Dr. and Cactus Rd.	NB
5	Shea Blvd. and Mountain View Rd.	NB
6	Shea Blvd. and Mountain View Rd.	SB

The speed limit on this stretch of the SR 101 freeway is 65 mph, and the enforcement equipment is set to photograph drivers when they are traveling at 76 mph or faster. As discussed, the SEP began on January 22, 2006 and ended on October 23, 2006. For the first 30 days of the program, the city sent warning notices to drivers who exceeded the 76 mph threshold. The cameras were operated for a total of 275 days:

- Warning period: 1/22/2006 – 2/21/2006 (31 days)
- Program period: 2/22/2006 –10/23/2006 (244 days)

Vehicle speed is determined by measuring the time it takes a vehicle to travel from the first sensor to the last sensor on the detection zone installed at each enforcement site. The Redflex system uses the known distance between the sensors and the measured time to calculate speed. Of course time is measured precisely in order to estimate speeds precisely.

Chapter 2 Literature Review

In this chapter, previous studies on the effect of speed enforcement cameras are summarized, and the lessons and issues raised by literature that could affect study consideration are discussed. As of 2005, at least 75 countries rely on such cameras to enforce speed limits, especially on high-risk roads, including Australia, Austria, Canada, Germany, Greece, Italy, the Netherlands, Norway, Singapore, South Africa, South Korea, Spain, Switzerland, and Taiwan. Although speed enforcement cameras have frequently been used in the United States, their use has been limited (i.e., not at fixed-site) compared to other countries. Cameras currently are being used in several states, including Arizona, California, Colorado, North Carolina, Ohio, Oregon, and the District of Columbia (Roberts and brown-Esplain, 2005). Out of numerous studies conducted in these countries and nation, all possible studies of relevance were initially identified on the basis of internet journal database searches. Then, a number of "critical studies,"—appropriate in terms of methodological rigor and frequently cited by other researchers or in discussions of speed enforcement effectiveness, are examined. Extracted from the critical studies is general information on the effects of speed enforcement cameras and issues that need to be considered in this study.

2.1 Studies for Speed Enforcement Cameras on Freeways

Several studies have evaluated the impacts of speed enforcement cameras on speed and safety in freeways. Lamm and Kloeckner (1984) assessed the effects of fixed automated cameras at autobahn in Germany. In addition to a reduction of about 12.4 mph in speed, the accident frequency decreases from "200 accidents/year" to "84 accidents/year," and the number of fatal and injury accidents are reduced from "80 accidents/year" to "30 accidents/year."

Chen *et al.* (2002) evaluated the effects of mobile cameras on highway 17 in British Columbia in Canada. By using the simple before and after study, they reveal that the mean speed at the deployment locations is reduced to below the posted speed limit. Overall, the mean speed decreased by approximately 1.74 mph, representing a 3% reduction, and the standard deviation of speed declined by 0.3 mph (6% reduction).

Some studies on freeways focused on the spillover effects—time or distance halo effects— rather than the direct effects. The time halo effect is defined as the length of time during which the effect of enforcement is still present after enforcement activity has been withdrawn. The distance halo effect is the number of kilometers from the enforcement site, in which the effect is maintained (Hauer et al., 1982;Vaa, 1997). Sisiopiku and Patel (1999) analyzed both time and distance halo effects of mobile speed cameras on I-96 in Ionia County, Michigan. The average speed just upstream of the police car's location were reduced, but as soon as vehicles passed the patrol car, drivers accelerate to their normal speeds or more, but no "time halo" effects on the vehicles at the increased speed zone were observed.

Ha *et al.* (2003) investigated the distance halo effects using speed data collected from 7 measurement sites on urban highway in South Korea. Drivers tended to reduce their speeds when approaching the speed enforcement camera, but drivers accelerated back to their original speeds on passing the enforcement camera—thus no evidence of distance spill-over effects were observed.

Champness and Folkman (2005) also examined the time and distance halo effects of mobile overt speed cameras in Australia. Time and distance halo effects were analyzed using numerous measurements: mean speeds, 85th, 90th and 95th percentile speeds, etc. Distance halo effects were clearly identifiable, with an observed reduction in speeds one kilometer downstream, but the magnitude of the reduction diminishing at 500 meters downstream of the camera site. The effect of the speed camera was completely dissipated at 1.5 kilometers downstream.

Another study attempted to compare the reduction in speed in terms of enforcement type and time delay in the case of mailed fines on 75 mph motorway in Netherlands (Waard and Rooijers, 1994). Two field experiments were conducted to establish the most effective method of enforcement in reducing driving speeds. The enforcement intensity study showed a clear relationship between intensity level of enforcement and the proportion of speeding drivers. The highest intensity levels led to the largest and longest lasting reduction in driving speeds, but effects on average driving speeds of the methods on-view stopping versus photographing of offenders were similar.

Table 2: Summary of studies on freeway

Reference	Country	Camera type	Enforcement sites	Posted speed limits
(Lamm and Kloeckner, 1984)	Germany	Fixed	2 sites on Autobahn	62 mph (100kph)
(Waard and Rooijers, 1994)	Netherlands	Mobile	6 sites on motorways	75 mph (120kph)
(Sisiopiku and Patel, 1999)	US	Mobile	29-mile segment on I 96, Michigan.	70mph (113kph)
(Chen *et al.*, 2002)	Canada	Mobile	12 sites on Highway 17	56mph (90kph)
(Ha *et al.*, 2003)	South Korea	Fixed	1 site on urban highway	50mph (80kph)
(Champness and Folkman, 2005)	Australia	Mobile	1 site Highway section, Queensland	62 mph (100kph)

Table 2 summarized the experimental details of these studies. Only two studies (Lamm and Kloeckner, 1984; Ha *et al.*, 2003) are similar to the Scottsdale's enforcement environment (i.e., fixed camera). However, highways in Germany and South Korea are likely to have different traffic conditions, road users (skills and 'safety culture'), geometric design standards, and weather compared from the Scottsdale Loop 101. In fact, the cameras on Autobahn were deployed at steep downgrade sections (5% grade).

2.2 Studies for Speed Enforcement Cameras on non-Freeways

While there were relatively few studies for the speed enforcement cameras on freeway, a number of studies analyzed the effects of speed cameras on non-freeway roads. Table 3 shows the summary of outline of these studies.

Table 3: Summary of outline of studies on non-freeway

Reference	Country	Camera type	Enforcement sites	Posted speed limits
(Hauer *et al.*, 1982)	Canada	Fixed	4 sites on suburban two-lane road	37 mph (60kph) or 50mph (80kph)
(Vaa, 1997)	Norway	Fixed and Mobile	Roadway 22 and 170 in Norway (suburban two-lane road)	37 mph (60kph) or 50mph (80kph)
(Elvik, 1997)	Norway	Fixed	64 sites	31 mph (50kph) to 56mph (90kph)
(Retting and Farmer, 2003)	US	Mobile	7 sites on surface streets in Washington D.C.	25 mph or 30 mph
(Hess and Polak, 2003;Hess, 2004)	UK	Fixed	43 (49) sites on rural road	Speed limits vary from sites
(Goldenbeld and van Schagen, 2005)	Netherlands	Mobile	28 sites on rural road	50 mph (80kph) or 62 mph (100kph)
(Cunningham *et al.*, 2005)	US	Mobile	14 sites in City of Charlotte, North Carolina	25 mph to 55mph

Elvik (1997) assessed the effects of 64 fixed speed enforcement cameras in Norway on safety. The study controlled for general trends in the number of accidents and regression to the mean bias by using comparison groups and empirical Bayesian estimation respectively. The injury accidents were significantly reduced by 20%, and the property damage-only accidents were reduced by 12%. However, the reduction in the PDO accidents was not statistically significant.

Retting and Farmer (2003) evaluated the effects of mobile speed enforcements on speed at 7 sites in Washington D.C. With 8 comparison sites in Baltimore, Maryland, speed data collected 1 year before enforcement and approximately 6 months after enforcement began were analyzed. Mean speeds at 7 sites decline by 14%, and the proportion of vehicles exceeding the speed limit by more than 10 mph declined by 82%.

Goldenbeld and Schagen (2005) assessed the impacts of mobile inconspicuous speed cameras on the speed and safety at 28 enforcement sites in the Netherlands. With 15 sites on 80kph rural roads and all other non-enforced roads outside urban areas as comparison sites, the evaluation was performed. The results show that the mean speed decreased by 4kph on the enforced roads and by .5kph on the non-enforced comparison roads during the enforcement period. With regard to reduction in safety, the number of road accidents and casualties decreased by 21%.

Again, there are several studies focusing on the spillover effects. Hauer *et al.* (1982) attempted to investigate both spillover effects (i.e., time halo and distance halo effects) comprehensively. The distance halo effects were measured at 4 enforcement sites with upstream and downstream measurement sites, which are located on semi-rural two land roads in Halton and Peel counties west of Metropolitan Toronto. To investigate "time halo" effects, speeds were monitored prior to, during, and after exposure to enforcement. The investigation on aggregate speed distributions suggested that the average speed of the free flowing vehicles was remarkably reduced at the enforcement site. When enforcement was in place, the average speed at the site was close to the posted speed limit. The downstream distance halo effect follows the general form of exponential decay, representing that the effect of enforcement is reduced by half for approximately every 900 meters. The "time halo" appeared to be the only phenomenon to be affected by the intensity of enforcement: the effect of enforcement at single day is disappeared after 3 days, while enforcement on several consecutive days had a longer term effect.

Vaa (1994) also investigated the impacts of the intensity level of speed enforcement on speeds. Speed was measured at 12 sites in Norway consecutively for 16 weeks: 2 before weeks, 6 enforcement weeks, and 8 after weeks. They concluded that the average speeds during the enforcement period were reduced, but durations for time-halo effects were influenced by the intensity of the enforcement, which were consistent with other results (Hauer *et al.*, 1982;Waard and Rooijers, 1994).

Hess (2004) assessed the effects of 49 fixed speed enforcement cameras in Cambridgeshire, U.K. Two consecutive studies (Hess and Polak, 2003;Hess, 2004) were conducted in order to quantify the performance of the cameras in terms of their catchment area (the effects of cameras for various ranges around the cameras). In the 250-meter range, injury accident numbers were reduced by 45.74%. However, the reductions in the 500-, 1,000-, and 2,000-meter ranges decreased by 41.30%, 31.62%, and 20.86% respectively.

2.3 Summary of Findings

A number of studies have evaluated the effects of speed enforcement cameras on safety and speed. Some studies evaluated the effects on speed or traffic safety solely, while others evaluated both. In addition, several studies focused on the spillover effects in terms of time and space. Not surprisingly, the estimates of the safety effect of speed cameras vary considerably, even though all studies suggest that photo enforcement cameras are effective in reducing speed and crash frequency at photo enforcement camera deployment sites. A recent meta analysis (Pilkington and Kinra, 2005) also suggests that speed cameras are an effective means of reducing road traffic collisions and related causalities.

However, many studies suffer from one or more non-ideal conditions. For example, the results of some studies may under/overestimate the effects of the speed enforcement cameras on traffic safety since total instead of target crashes (crashes that are materially affected by the photo enforcement speed cameras) were analyzed. In addition, failure to account for regression-to-the-mean can overestimate the positive effects, while benefits can be underestimated if spillover effects are ignored. From the literature review several noteworthy observations are relevant:

- *Defining Target crashes*: The lack of precise definition in past studies could have led to the under estimation of the safety effects.
- *Minimizing "spillover effects" in selecting comparison/control sites*: If crashes at control/comparison sites are affected by the demonstration program, estimating the program effect at the treated enforcement zone becomes more difficult.
- *Exposure changes between the before and program periods*: It is important to account for changes in traffic exposure between the before and program periods.

- *Regression to the mean effects*: In many studies, speed enforcement cameras were installed at high-crash sites—which could lead to significant regression to the mean bias that needs to be accounted for—often leading to over-estimation of safety impacts.
- *Effects of speed enforcement cameras on violation frequency*: Since the direct effect of speed cameras is a reduction in speeding, it is expected that violations should decrease, thereby reducing relevant crashes. However, if this assumption does not hold, the speed enforcement countermeasure could be invalid.
- *Spillover effects:* Two spillover effects (i.e., distance and time spillover effects) need to be investigated when analyzing the program effect.

Chapter 3 Effects of the SEP on Speeding Behavior and Speed

In this chapter, the effects of the SEP on speeding behavior and speed are examined. The speeding behavior is analyzed by comparing the detection frequencies during the *warning*, *program*, and *after* periods, collected at the 6 enforcement camera locations, and the impact on speed was compared by analyzing the mean speeds during the *before* and *program* periods. The detection frequency data were obtained from Redflex, while the average speed data were obtained from ADOT. In the following sections, all relevant analysis results are discussed in detail.

3.1 Changes in the Detection Frequency

3.1.1 Data Description

The detection frequency data used in this analysis are the number of vehicles detected by the 6 enforcement cameras, which were collected for 46 weeks (1/22/2006 – 12/3/2006: 316 days). In order to compare the detection frequency by time periods, three time periods were used:

- *warning* period: 1/22/2006 – 2/21/2006 (31 days)
- *program* period: 2/22/2006 –10/23/2006 (244 days)
- *after* period: 10/24/2006 – 12/3/2006 (41 days)

Note that no detection data were collected prior to the *warning* period.

Table 4 shows the summary statistics of the average detection frequency for the 3 periods, and the interval plot for the mean detection frequencies with 95% CIs is shown in Figure 2.

Table 4: Summary statistics for the average daily detection frequency by site and period

	Warning period (N=31 days)		Program period (N=244 days)		After period (N=41 days)	
Site	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
1	203.52	84.08	158.41	62.08	1366.68	541.18
2	117.16	47.1	87.2	34.96	999.29	442.07
3	245.42	80.47	254.76	78.93	2341.9	968.51
4	38.84	19.53	31.09	18.3	382.17	214.73
5	186.32	71.68	132.39	58.03	1620.46	857.15
6	181.94	78.27	114.35	57.66	847.76	496.22
Mean	162.2	94.57	129.7	88.06	1259.71	888.17

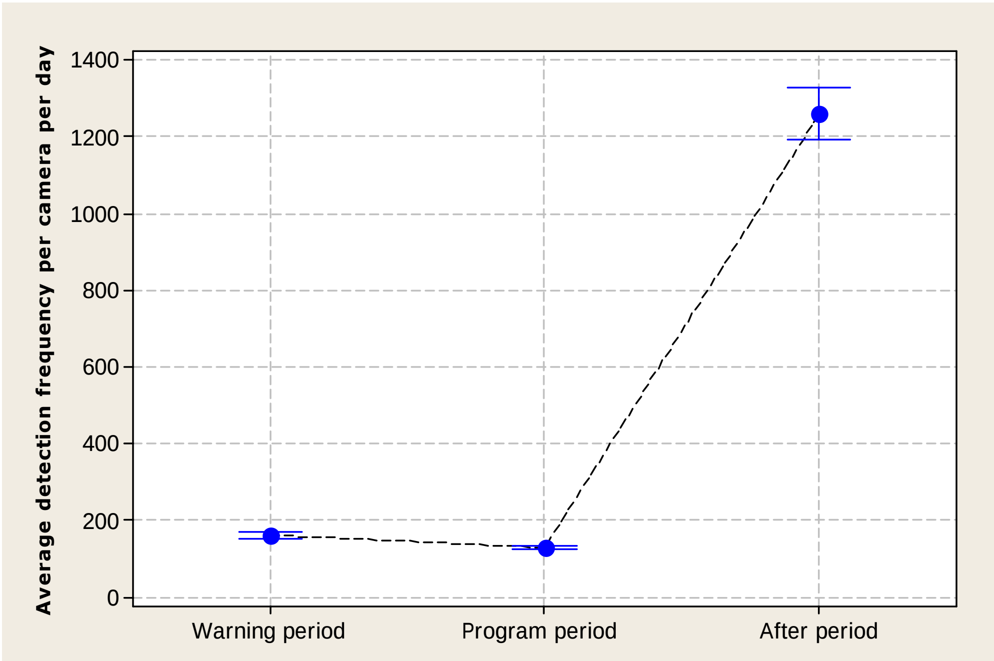


Figure 2: Average daily detection frequency by period

The detection frequencies vary over the enforcement sites—the detection frequencies at site 3 (see Table 1: Frank Lloyd Wright Blvd. and Raintree Dr.) are greater than those at other sites (see Figure 3). Consequently, the summary statistics in Table 4 show that both the period and site effects for the detection frequency exist.

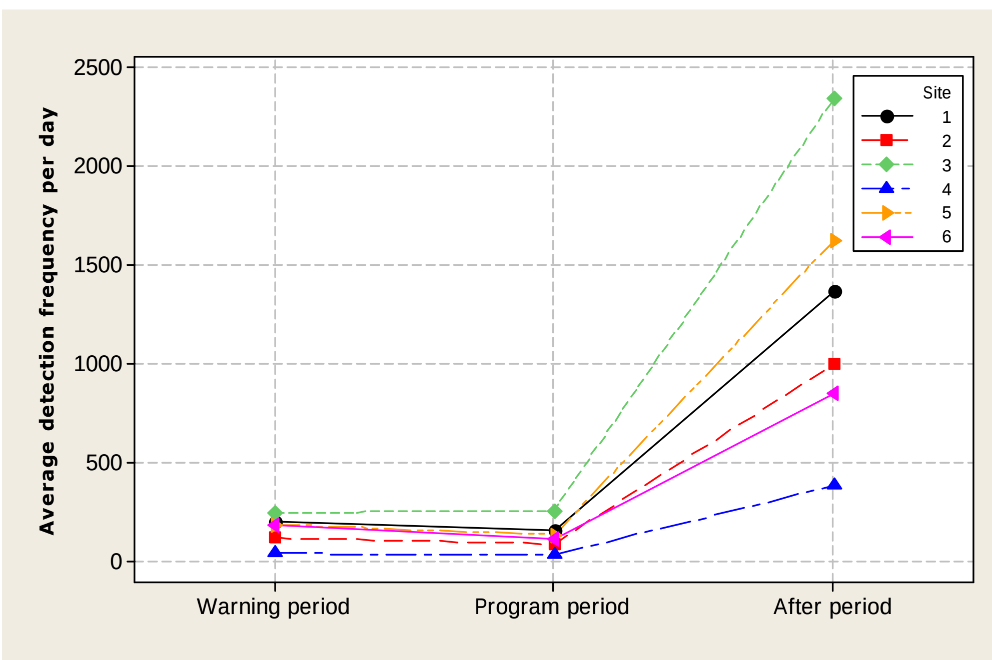


Figure 3: Average daily detection frequency by period and site

Table 5: Summary statistics for the daily detection frequency by day of week and period

	Warning period			Program period			After period		
	Mean	Std.Dev.	N[1]	Mean	Std.Dev.	N	Mean	Std.Dev.	N
Monday	127.67	61.59	24	107.08	66.81	186	1012.47	612.96	30
Tuesday	130.87	61.35	30	98.22	62.98	198	914.75	692.35	36
Wednesday	125.79	57.69	24	99.88	66.13	210	987.53	811.47	36
Thursday	123.75	71.05	24	101.63	66.09	210	905.20	611.42	30
Friday	140.08	77.88	24	114.09	76.49	210	1010.83	729.05	24
Saturday	211.61	92.52	18	188.11	104.02	186	1704.96	1069.35	24
Sunday	223.00	111.41	24	188.88	100.09	186	1694.38	877.84	24
Holiday	259.28	122.64	18	181.03	91.66	78	1857.93	951.16	42
Total	162.20	94.57	186	129.70	88.06	1464	1259.71	888.17	246

In addition, the time series plots illustrated in Figure 5 and Figure 8 show that the detection frequency has periodic patterns–spikes for weekends and holidays. Table 5 shows the summary statistics for the detection frequency per camera per day during the 3 periods by day of week, in which the list of holidays used in this analysis is summarized in Table 6. The detection frequencies during weekends and holidays are relatively greater than those during weekdays, while the detection frequencies during weekdays seem to be similar to each other (see Table 5).

Table 6: A list of holidays in 2006

Description	Official observed date	Holiday	
		Start	End
New Year's Day	Monday, January 2*	December 31, 2005	January 2, 2006
Birthday of Martin Luther King, Jr.	Monday, January 16	January 14, 2006	January 16, 2006
Washington's Birthday	Monday, February 20**	February 18, 2006	February 20, 2006
Memorial Day	Monday, May 29	May 27, 2006	May 29, 2006
Independence Day	Tuesday, July 4	July 1, 2006	July 4, 2006
Labor Day	Monday, September 4	September 2, 2006	September 4, 2006
Columbus Day	Monday, October 9	October 7, 2006	October 9, 2006
Veterans Day	Friday, November 10***	November 10, 2006	November 12, 2006
Thanksgiving Day	Thursday, November 23	November 23, 2006	November 26, 2006
Christmas Day	Monday, December 25	December 23, 2006	December 25, 2006

Table 7 shows the summary statistics for the average daily detection frequency per camera during the 3 periods, in which each day is aggregated by 2 categories: "weekdays" and "weekends and holidays." Regardless of the periods, detection frequencies during weekends and holidays are greater than those during weekdays as shown in Figure 4. This finding suggests that the detection frequency needs to be analyzed by controlling for the day of week effect.

[1] The sample size N indicates total number of Mondays during the warning period times the demonstration sties (6 Mondays×6 sites= 24).

Table 7: Summary statistics for the daily detection frequency during the 3 periods by the 2 categories

	Warning period			Program period			After period		
	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N
Weekdays	129.69	65.27	126	104.18	68.05	1014	963.28	691.52	156
Weekends and holidays	230.47	109.65	60	187.20	100.17	450	1773.52	957.99	90
Total	162.20	94.57	186	129.70	88.06	1464	1259.71	888.17	246

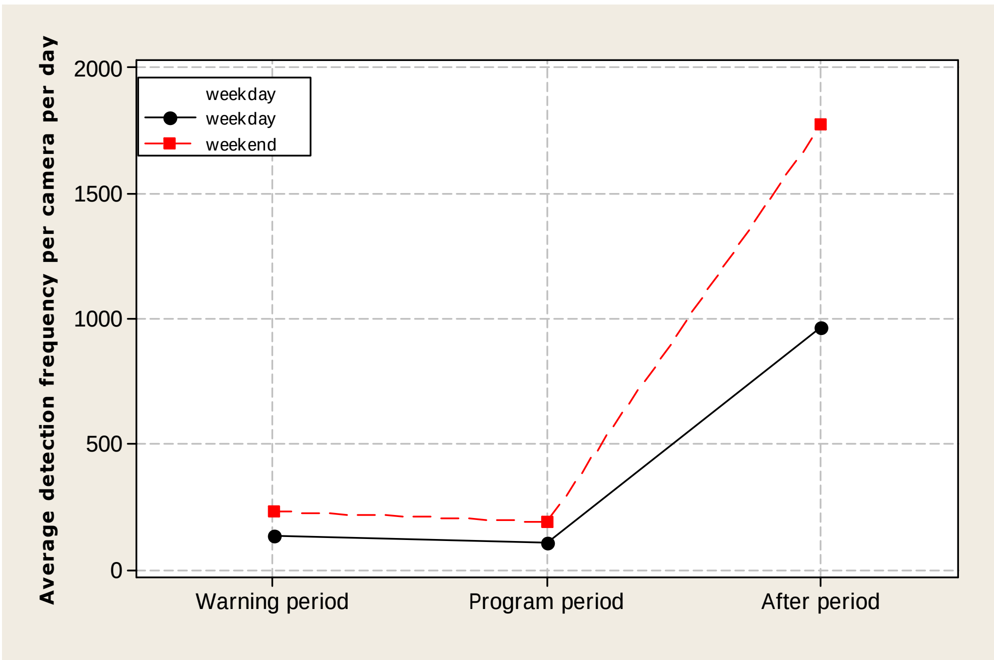


Figure 4: Average daily detection frequency by periods and day of week

The time series plots also suggest that the day of week is one of several important factors that affect the detection frequency. As previously discussed, the time series plots have periodical spikes when weekends and holidays are not excluded (see Figure 5 and Figure 8). However, more stable time series plots can be obtained when the day of week effects are eliminated from the time series plots (see Figure 6, Figure 7, Figure 8, Figure 9, and Figure 10).

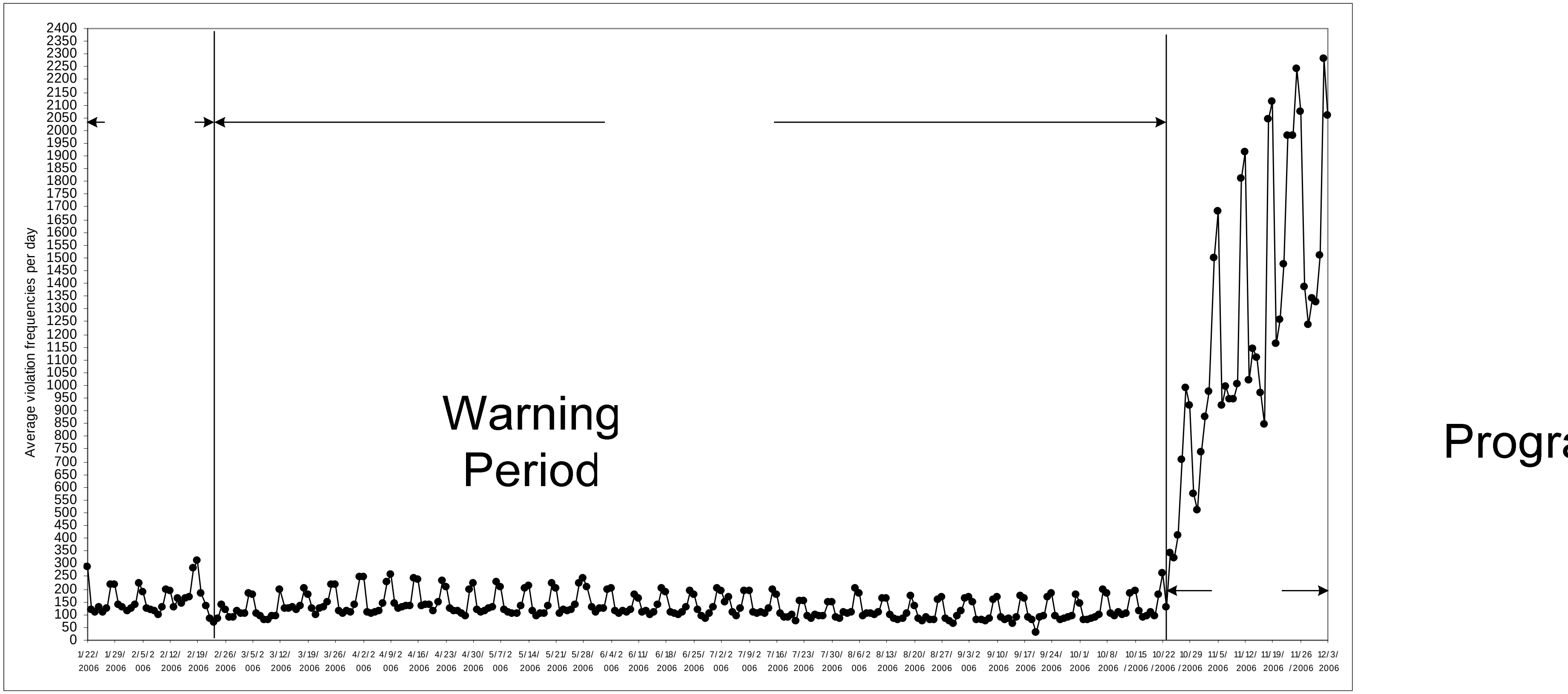


Figure 5: Average detection frequency per camera per day during the 3 periods

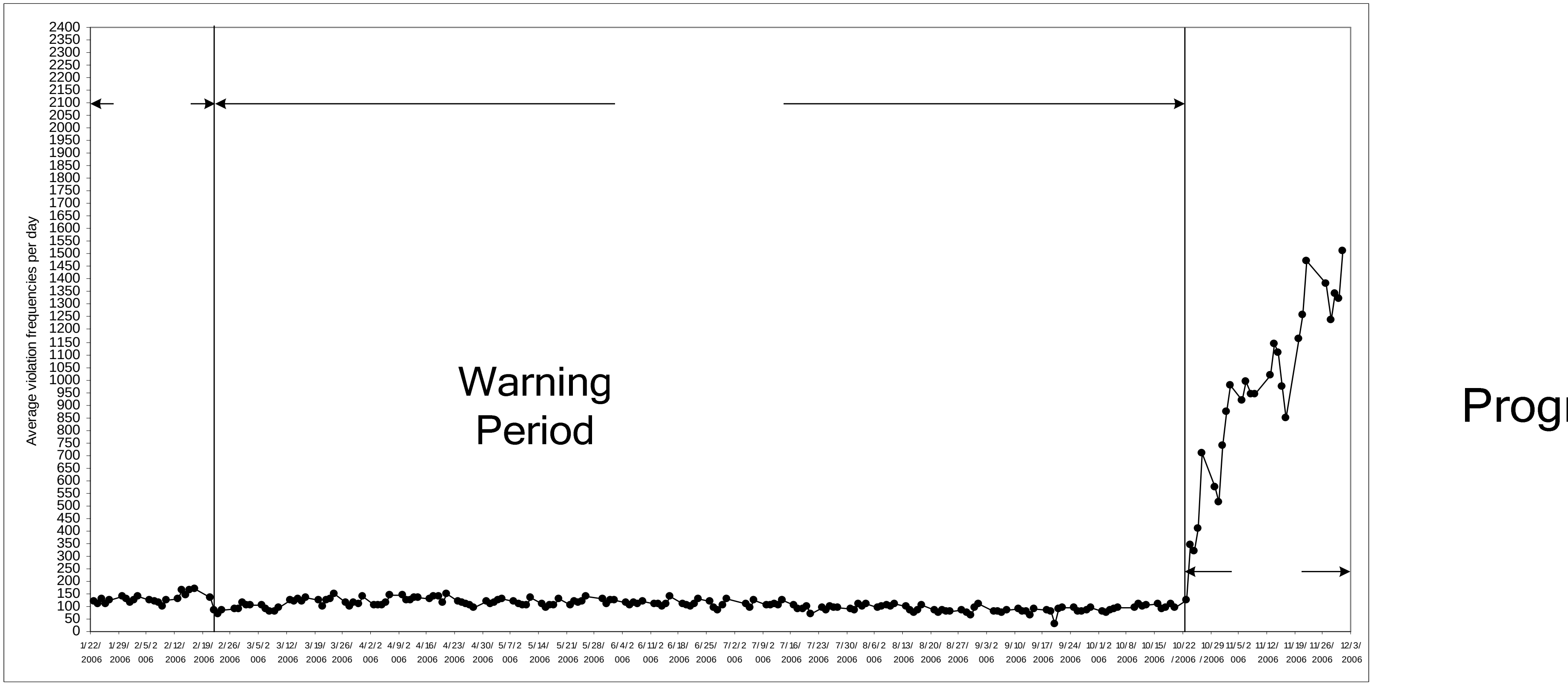


Figure 6: Average detection frequency per camera per day during the 3 periods (weekday)

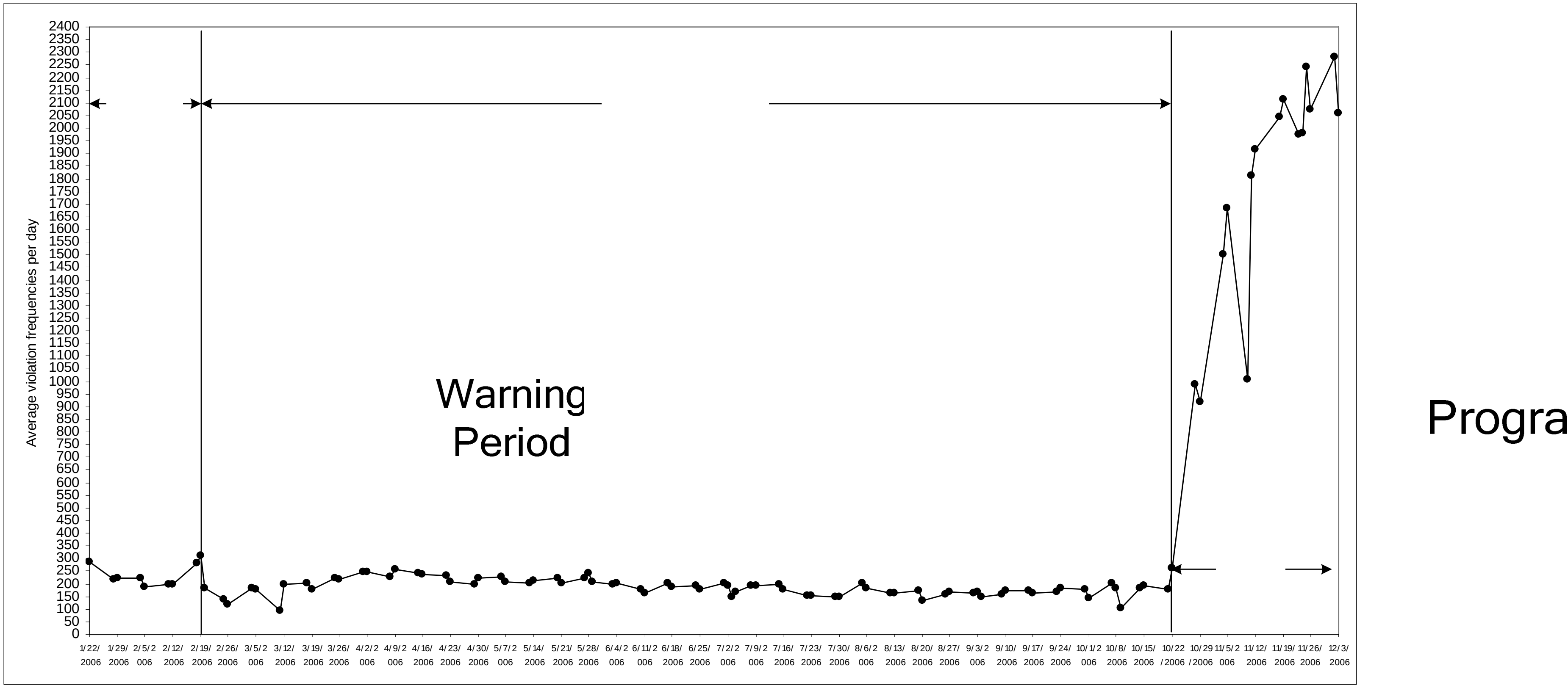


Figure 7: Average detection frequency per camera per day during the 3 periods (weekend and holiday)

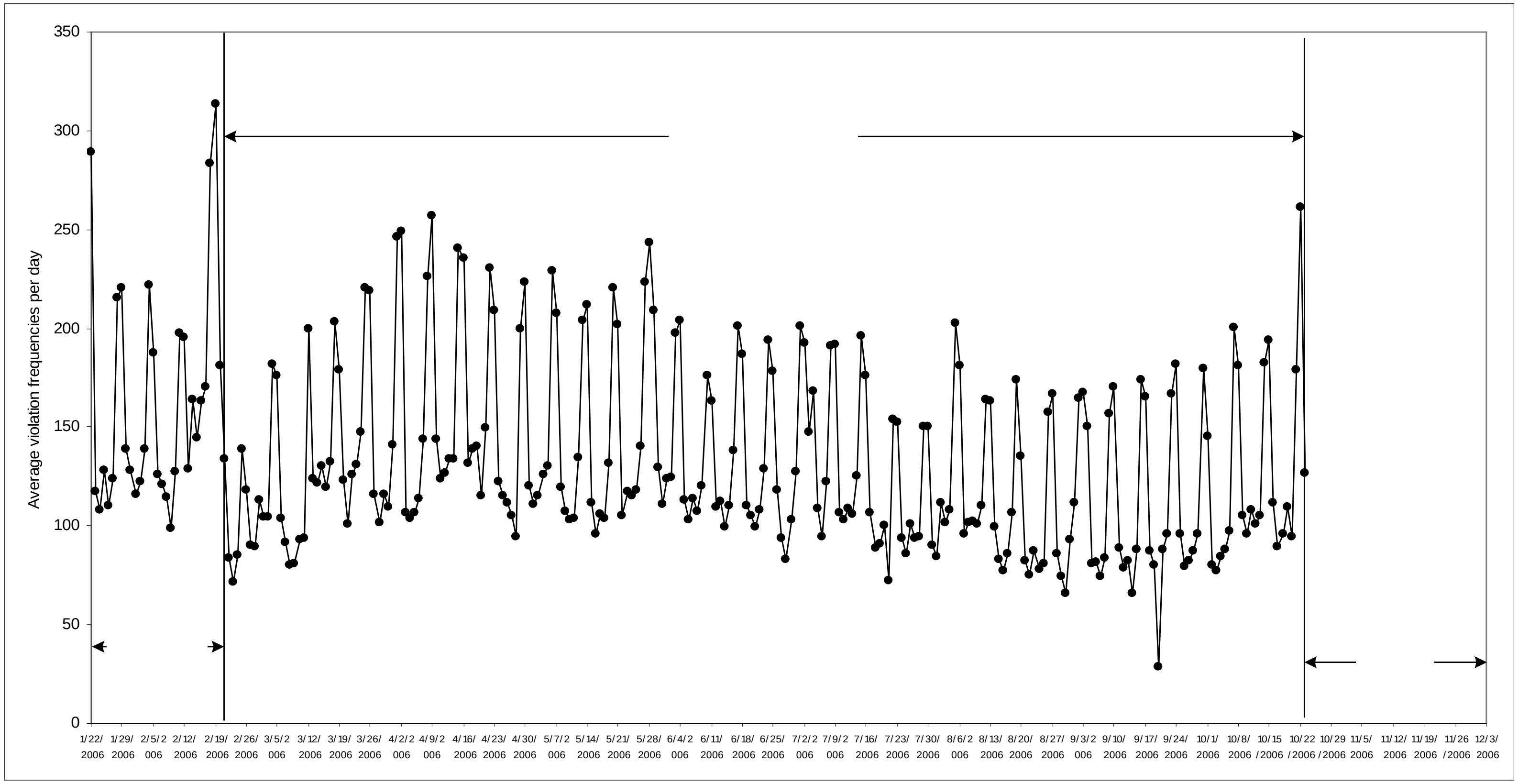


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Figure 8: Average detection frequency per camera per day during the warning and program periods

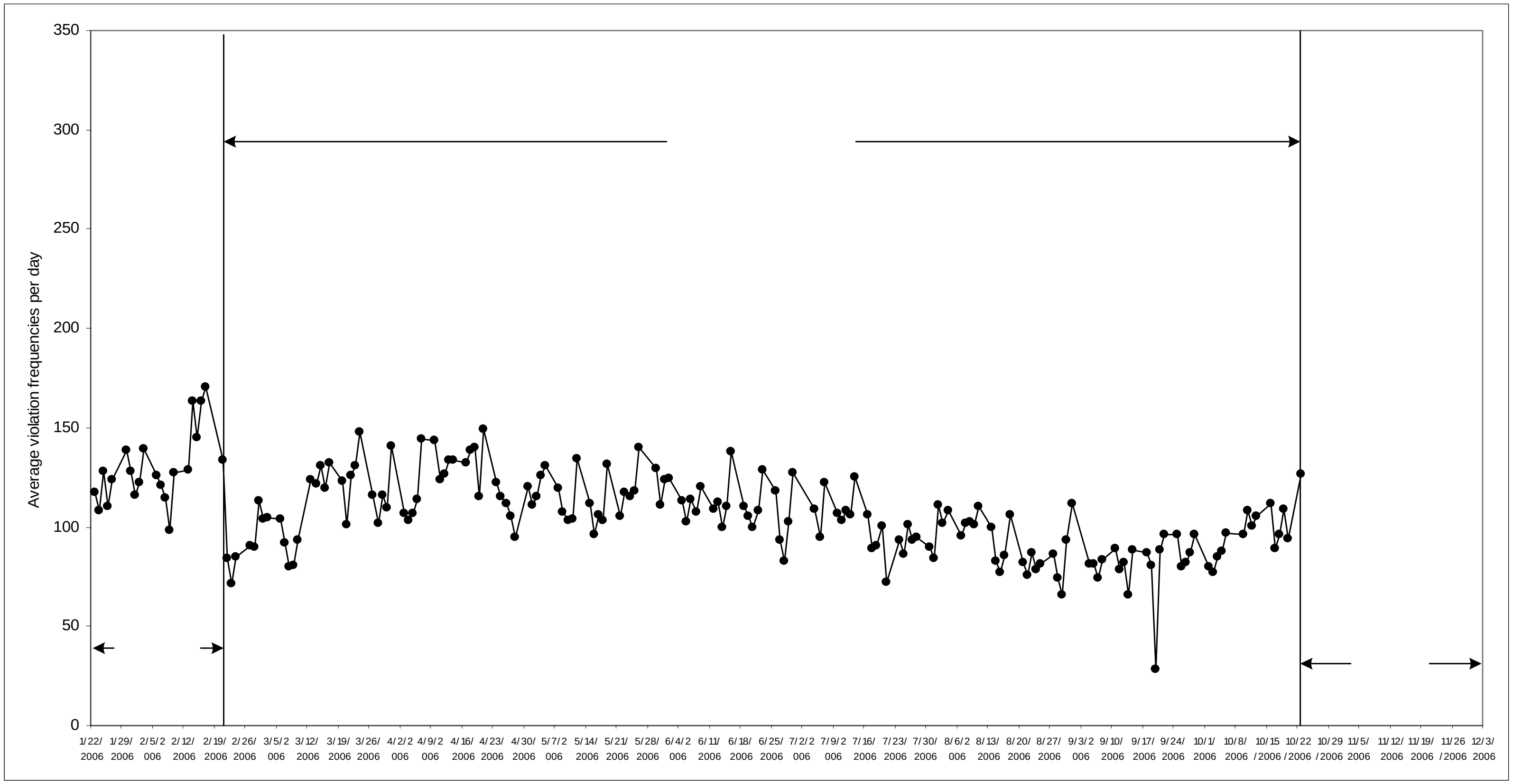

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Figure 9: Average detection frequency per camera per day during the warning and program periods (weekday)

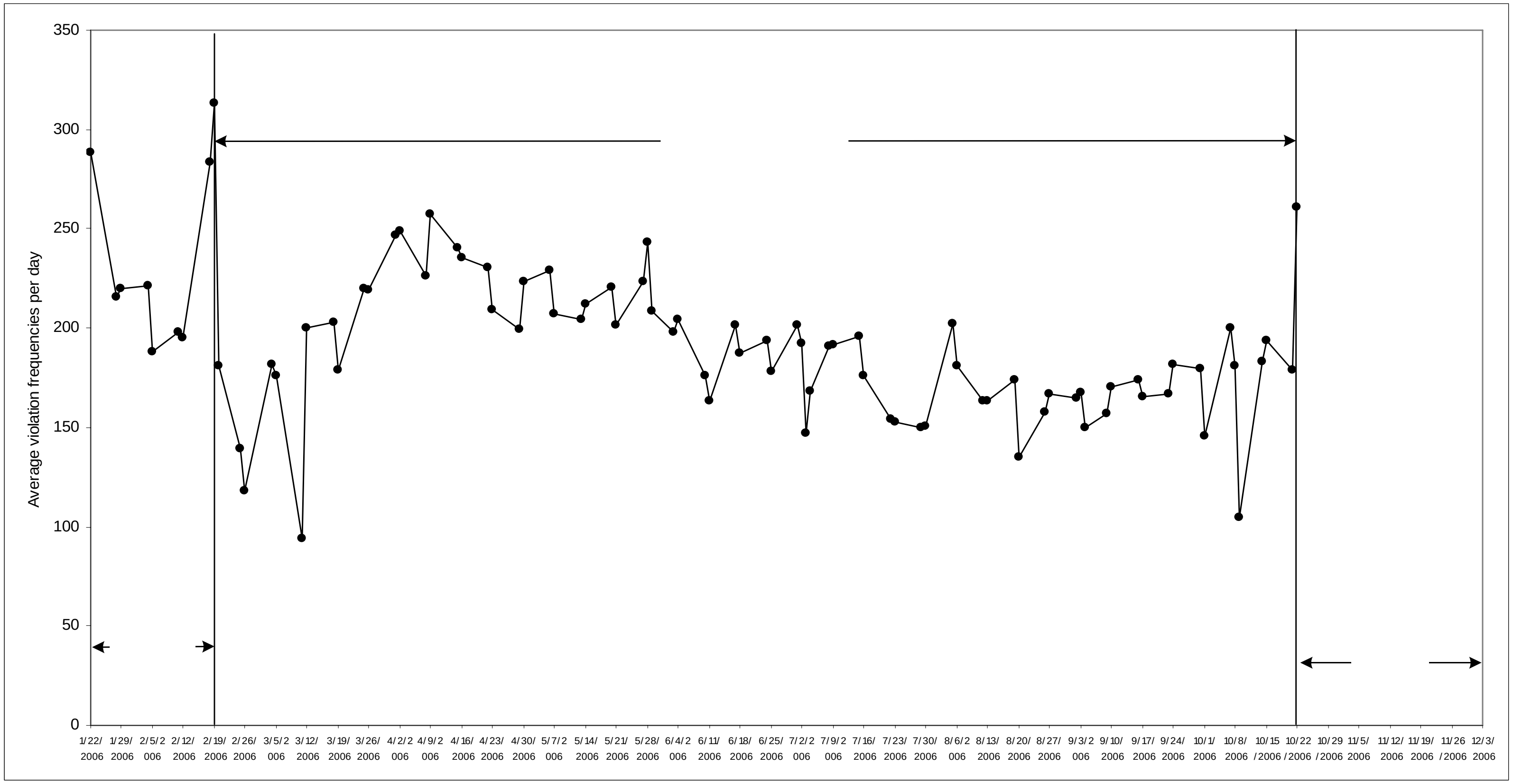

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Figure 10: Average detection frequency per camera per day during the warning and program periods (weekend)

3.1.2 Effects of SEP on the Detection Frequencies

3.1.2.1 Relationship between the Day of Week and Detection Frequencies

The preliminary findings suggest that detection frequencies are affected by the presence of the SEP, day of week, and weekend/holiday effects. Consequently, we first analyze whether detection frequencies are statistically different by day of the week.

The 3 analysis of variance (ANOVA) models summarized in Table 8 are used to investigate the day of week effects for the detection frequencies. The three models consist of the following:

- Model I: Two-factor ANOVA model using all periods
    - Factor A: The 3 periods (3 levels)
    - Factor B: Day of week (7 levels)
- Model II: Two-factor ANOVA model using all periods
    - Factor A: The 3 time periods (3 levels)
    - Factor B: Day of week and holiday (8 levels)
- Model III: Two-factor ANOVA model excluding the after period
    - Factor A: The 2 periods (2 levels)
    - Factor B: Day of week and holiday (8 levels)

Table 8: Preliminary ANOVA model results

Model	Source	DF	Seq SS	Adj SS	Adj MS	F	P	R^2
Model I	Period	2	271771764	271268992	135634496	1319.59	<.0001	0.59
	Day of week	6	12312285	12312285	2052047	19.96	<.0001	
	Error	1887	193955507	193955507	102785			
	Total	1895	478039556					
Model II	Period	2	271771764	254762692	127381346	1263.71	<.0001	0.60
	Day of week	7	16160536	16160536	2308648	22.9	<.0001	
	Error	1886	190107256	190107256	100799			
	Total	1895	478039556					
Model III	Period	1	174303	160750	160750	25.33	<.0001	0.20
	Day of week	7	2586658	2586658	369523	58.23	<.0001	
	Error	1641	10413067	10413067	6346			
	Total	1649	13174028					

The ANOVA model results in Table 8 show that the two factors are significant in all models at α=0.05. Note that the adjusted sum of squares (denoted as Adj SS) is used to conduct F-tests because the data are not balanced. Thus, detection frequencies are significantly associated with the two factors: the time period (*warning*, *program*, and *after*) and day of the week.

In addition, Tukey's pairwise comparisons are used to test whether or not the mean detection frequencies of each treatment level (e.g., day of week) are statistically different from each other. Table 9 shows the Tukey's pairwise comparison matrix, in which the null hypothesis is that the mean detection frequencies of the 2 days (a pair) are the same. Thus, if the p-value in a cell of the comparison matrix is less than a significance level (α=0.05), we could conclude that the difference in the mean detection frequencies of the 2 associated days is statistically significant (i.e., they are statistically not the same). For example, the p-value for Monday and Tuesday in the Model I (0.9505) indicates that the mean detection frequencies between Mondays and Tuesdays are not statistically different, while the p-value for Monday and Saturday in the Model I (<0.0001) indicates that the mean detection frequencies between Mondays and Saturdays are statistically different.

Table 9: Tukey pairwise comparison matrix with associated p-values

Model I	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	
Monday		0.9505	0.9932	1.000	0.9953	<.0001	<.0001	
Tuesday	0.9505		0.9999	0.9815	0.6429	<.0001	<.0001	
Wednesday	0.9932	0.9999		0.9988	0.8357	<.0001	<.0001	
Thursday	1	0.9815	0.9988		0.9822	<.0001	<.0001	
Friday	0.9953	0.6429	0.8357	0.9822		<.0001	<.0001	
Saturday	<.0001	<.0001	<.0001	<.0001	<.0001		1.000	
Sunday	<.0001	<.0001	<.0001	<.0001	<.0001	1.000		
Model II	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Holiday
Monday		0.9944	0.9999	0.9996	0.9998	<.0001	<.0001	<.0001
Tuesday	0.9944		0.9999	1.000	0.9124	<.0001	<.0001	<.0001
Wednesday	0.9999	0.9999		1.000	0.9891	<.0001	<.0001	<.0001
Thursday	0.9996	1.000	1.000		0.9749	<.0001	<.0001	<.0001
Friday	0.9998	0.9124	0.9891	0.9749		<.0001	<.0001	<.0001
Saturday	<.0001	<.0001	<.0001	<.0001	<.0001		1.000	0.0041
Sunday	<.0001	<.0001	<.0001	<.0001	<.0001	1.000		0.0037
Holiday	<.0001	<.0001	<.0001	<.0001	<.0001	0.0041	0.0037	
Model III	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Holiday
Monday		0.9774	0.9892	0.9974	0.9722	<.0001	<.0001	<.0001
Tuesday	0.9774		1.000	1.000	0.4532	<.0001	<.0001	<.0001
Wednesday	0.9892	1.000		1.000	0.5298	<.0001	<.0001	<.0001
Thursday	0.9974	1.000	1.000		0.6568	<.0001	<.0001	<.0001
Friday	0.9722	0.4532	0.5298	0.6568		<.0001	<.0001	<.0001
Saturday	<.0001	<.0001	<.0001	<.0001	<.0001		1.000	1.000
Sunday	<.0001	<.0001	<.0001	<.0001	<.0001	1.000		1.000
Holiday	<.0001	<.0001	<.0001	<.0001	<.0001	1.000	1.000	

Note: "H_0: The difference in the mean detection frequencies between two days is zero."

In Model I, the difference in the mean detection frequencies between Saturdays and Sundays is not significant (the 95% confidence interval for the difference is [–79.03, 82.99]; see Table 10). In addition, the mean detection frequency differences during weekdays are not statistically significant. However, the mean detection frequencies between weekdays and weekends are significantly different, in which the associated p-values are less than 0.001 as shown in Table 9.

In Model II, the Tukey's pairwise comparison matrix yields similar results: the mean detection frequencies for all weekdays are significantly different from those for weekends or holidays, while there is no significant difference in the mean detection frequencies between weekdays. However, the mean detection frequencies for holidays are not the same as those for Saturdays and Sundays. Since the significant difference might stem from the interaction between the periods and holiday effects, we reanalyzed the effect of holidays on the mean detection frequency by excluding the after period (see the results of Model III).

Model III also yields similar results: no difference in the mean detection frequencies between weekdays and significant difference in the mean detection frequencies between weekdays and weekends/holidays. Unlike the results in Model II, the mean detection frequency for holidays is not significantly different from the detection frequencies of weekends. Note that the difference in the mean detection frequencies between weekends and holidays is very small (–2.41 and –0.63; see Table 10).

The ANOVA model results show that the mean detection frequencies are significantly associated with the day of week as well as the time period of observation. Although the factor (i.e., the day of week) can be included in the analysis as a separate factor, the 2 sub-samples were used in the analyses discussed in the next subsection in order to develop parsimonious models.

Table 10: Differences in means and simultaneous 95% CI

Model I					Model II					Model III				
Group A	Group B	Difference in means	95% CIs Lower	95% CIs Upper	Group A	Group B	Difference in means	95% CIs Lower	95% CIs Upper	Group A	Group B	Difference in means	95% CIs Lower	95% CIs Upper
Monday	Tuesday	28.03	-53.42	109.49	Monday	Tuesday	21.95	-63.98	107.88	Monday	Tuesday	7.46	-15.67	30.58
Monday	Wednesday	19.04	-62.42	100.51	Monday	Wednesday	10.72	-74.75	96.19	Monday	Wednesday	6.53	-16.45	29.51
Monday	Thursday	5.02	-76.44	86.49	Monday	Thursday	14.56	-71.37	100.48	Monday	Thursday	5.17	-17.81	28.15
Monday	Friday	-17.78	-99.25	63.68	Monday	Friday	-13.17	-99.59	73.25	Monday	Friday	-7.69	-30.67	15.29
Monday	Saturday	-169.63	-251.10	-88.16	Monday	Saturday	-149.69	-238.81	-60.57	Monday	Saturday	-81.57	-105.34	-57.80
Monday	Sunday	-167.65	-248.66	-86.64	Monday	Sunday	-149.24	-237.75	-60.72	Monday	Sunday	-83.34	-106.94	-59.75
Tuesday	Wednesday	-8.99	-90.45	72.47	Monday	Holiday	-280.07	-383.76	-176.39	Monday	Holiday	-83.97	-113.79	-54.16
Tuesday	Thursday	-23.01	-104.46	58.45	Tuesday	Wednesday	-11.23	-94.64	72.17	Tuesday	Wednesday	-0.93	-23.43	21.57
Tuesday	Friday	-45.81	-127.27	35.64	Tuesday	Thursday	-7.39	-91.28	76.49	Tuesday	Thursday	-2.29	-24.79	20.22
Tuesday	Saturday	-197.66	-279.12	-116.20	Tuesday	Friday	-35.12	-119.53	49.29	Tuesday	Friday	-15.15	-37.65	7.36
Tuesday	Sunday	-195.68	-276.68	-114.68	Tuesday	Saturday	-171.64	-258.81	-84.47	Tuesday	Saturday	-89.02	-112.34	-65.71
Wednesday	Thursday	-14.02	-95.46	67.42	Tuesday	Sunday	-171.19	-257.72	-84.65	Tuesday	Sunday	-90.80	-113.92	-67.68
Wednesday	Friday	-36.83	-118.27	44.62	Tuesday	Holiday	-302.02	-403.87	-200.17	Tuesday	Holiday	-91.43	-120.86	-62.00
Wednesday	Saturday	-188.67	-270.12	-107.23	Wednesday	Thursday	3.84	-79.55	87.23	Wednesday	Thursday	-1.36	-23.71	20.99
Wednesday	Sunday	-186.69	-267.70	-105.68	Wednesday	Friday	-23.89	-107.80	60.03	Wednesday	Friday	-14.22	-36.57	8.13
Thursday	Friday	-22.81	-104.25	58.63	Wednesday	Saturday	-160.41	-247.08	-73.73	Wednesday	Saturday	-88.10	-111.25	-64.94
Thursday	Saturday	-174.66	-256.10	-93.21	Wednesday	Sunday	-159.95	-246.02	-73.88	Wednesday	Sunday	-89.87	-112.85	-66.89
Thursday	Sunday	-172.68	-253.69	-91.67	Wednesday	Holiday	-290.79	-392.35	-189.24	Wednesday	Holiday	-90.50	-119.85	-61.16
Friday	Saturday	-151.85	-233.29	-70.41	Thursday	Friday	-27.73	-112.07	56.62	Thursday	Friday	-12.86	-35.21	9.49
Friday	Sunday	-149.87	-230.88	-68.86	Thursday	Saturday	-164.24	-251.35	-77.14	Thursday	Saturday	-86.74	-109.90	-63.58
Saturday	Sunday	1.98	-79.03	82.99	Thursday	Sunday	-163.79	-250.29	-77.29	Thursday	Sunday	-88.51	-111.49	-65.53
					Thursday	Holiday	-294.63	-396.73	-192.53	Thursday	Holiday	-89.14	-118.49	-59.80
					Friday	Saturday	-136.52	-224.09	-48.94	Friday	Saturday	-73.88	-97.04	-50.72
					Friday	Sunday	-136.07	-223.04	-49.09	Friday	Sunday	-75.65	-98.63	-52.67
					Friday	Holiday	-266.90	-369.58	-164.23	Friday	Holiday	-76.28	-105.63	-46.94
					Saturday	Sunday	0.45	-89.21	90.12	Saturday	Sunday	-1.77	-25.55	22.00
					Saturday	Holiday	-130.39	-235.28	-25.49	Saturday	Holiday	-2.41	-32.39	27.57
					Sunday	Holiday	-130.84	-235.18	-26.50	Sunday	Holiday	-0.63	-30.45	29.18

3.1.2.2 Analysis Results

The effects of the SEP on detection frequencies were analyzed in terms of the 2 time periods ("Weekdays" and "Weekends and Holidays") as discussed in the previous subsection, and the fixed-effect ANOVA models were used for the 2 time periods. Since the site effects also exist, two factors (i.e., period and site) were used in the two-factor ANOVA models, in which the sites serve as blocks. In addition, the interaction between the block and the fixed factor *period* is included in the full model. Table 11 shows the ANOVA model results, in which all factors are significant at $\alpha=0.05$.

Table 11: ANOVA model results

Model	Source	DF	Seq SS	Adj SS	Adj MS	F	P	R^2
Weekday	Period	2	100686443	100686443	50343222	2058.99	<.0001	0.83
	Block (Site)	5	17274370	26633511	5326702	217.86	<.0001	
	Period*Site	10	30822283	30822283	3082228	126.06	<.0001	
	Error	1278	31247607	31247607	24450			
	Total	1295	180030703					
Weekend and Holiday	Period	2	191371652	191371652	95685826	2006.4	<.0001	0.90
	Block (Site)	5	21165487	29718887	5943777	124.63	<.0001	
	Period*Site	10	37973515	37973515	3797351	79.63	<.0001	
	Error	582	27755754	27755754	47690			
	Total	599	278266408					

Since our interest is in comparing the mean detection frequencies for each time period, the mean detection frequencies for each period shown in Table 12 are simultaneously compared. The Tukey's pairwise comparison method was again used, and the comparison results in Table 13 show that the difference in the mean detection frequencies between the warning and program periods is not significant (p-values are 0.1955 and 0.3203), while the mean detection frequencies of the *warning* and *program* periods are significantly different from those of the *after* period.

Table 12: Factor level means and 95% CI

Day of week	Period	Mean detection frequency	95% CIs	
			Lower	Upper
Weekday	Warning period	129.69	102.36	157.02
	Program period	104.18	94.55	113.82
	After period	963.28	938.72	987.84
Weekend and Holiday	Warning period	230.47	175.09	285.84
	Program period	187.20	166.98	207.42
	After period	1773.52	1728.31	1818.73

Table 13: Tukey pairwise comparison results

Day of week	Pair	Difference	P-value	95% CIs Lower	95% CIs Upper
Weekday	"Warning"–"Program"	25.51	0.1955	-9.15	60.17
	"Warning"–"After"	-833.59	<0.0001	-877.54	-789.64
	"Program"–"After"	-859.10	<0.0001	-890.65	-827.54
Weekend and Holiday	"Warning"–"Program"	43.27	0.3203	-27.26	113.79
	"Warning"–"After"	-1543.06	<0.0001	-1628.58	-1457.53
	"Program"–"After"	-1586.32	<0.0001	-1645.57	-1527.07

Using the Tukey pairwise comparison results, the relative changes are estimated and summarized in Table 14.

Table 14: Relative changes in the detection frequencies

Day of week	Pair	Difference	95% CIs Lower	95% CIs Upper
Weekday	"Warning"–"Program"	-0.20	-0.46	0.07
	"Warning"–"After"	6.43	6.09	6.77
	"Program"–"After"	8.25	7.94	8.55
Weekend and Holiday	"Warning"–"Program"	-0.19	-0.49	0.12
	"Warning"–"After"	6.70	6.32	7.07
	"Program"–"After"	8.47	8.16	8.79

The estimated results show that:

- After the SEP was implemented, the detection frequencies decreased by 20% (or 19%) from the *warning* to *program* period. However, the decrease in the detection frequencies is not statistically significant.
- After the SEP ended, the detection frequencies increased 825 % (or 847%) from the *program* to those in the *after* period.

3.2 Changes in the Mean Speed

In this section, the effects of the SEP on the mean speed are analyzed by comparing the mean speeds that were collected from the enforcement zone during the *before* and *program* periods. Unlike the analysis for the changes in the detection frequency, the mean speeds during the *after* period are not compared in this analysis due to incomplete data. The analysis was conducted using mean speeds during unconstrained traffic conditions, since traffic congestion will impact traffic speeds.

3.2.1 Data Description

In this subsection, the speed data obtained from the enforcement zone during the *before* period (see Table 15) are summarized, and the speed data during the *program* period are described in the analysis subsection.

Table 15: Description of the 6 measurement sites for the *before* period

ID	Direction	Location	Measurement date		
1	NB	CACTUS RD & SHEA BLVD	4/13/2005	4/14/2005	4/15/2005
2	SB	CACTUS RD & SHEA BLVD	4/13/2005	4/14/2005	4/15/2005
3	NB	RAINTREE DR & CACTUS RD	4/19/2005	4/20/2005	4/21/2005
4	SB	RAINTREE DR & CACTUS RD	4/19/2005	4/20/2005	4/21/2005
5	NB	SCOTTSDALE RD & PIMA/PRINCESS DR	6/27/2005	6/28/2005	6/29/2005
6	SB	SCOTTSDALE RD & PIMA/PRINCESS DR	6/27/2005	6/28/2005	6/29/2005

In order to reduce the variance from the different measurement dates, the middle of the day (24 hours) was consistently used in this analysis (i.e., 4/14/2005; 4/20/2005; 6/28/2005). The descriptive statistics for the speed data are summarized in Table 16, in which an individual speed data observation is the aggregated mean speed in each lane during 15 minute intervals. For instance, the mean speed at site *i* ($\overline{S_{i\bullet}}$) is estimated by the aggregated mean speed at site *i* during the jth interval (S_{ij}).

$$\overline{S_{i\bullet}} = \frac{\sum_{j=1}^{n_i} S_{ij}}{n_i}$$

where $i = 1, 2, \cdots, 6$ and $j = 1, 2, \cdots, n_i$.

Table 16: Summary of statistics for speed by site

Site ID	Mean	Std. Dev.	Min.	Median	Max.	N (n_i)
1	70.40	6.46	46	71	83	288
2	75.17	5.35	43	75	90	288
3	70.83	4.90	62	70	87	384
4	77.27	4.51	52	78	91	384
5	70.67	6.14	40	72	83	288
6	73.22	7.70	31	74	87	288

It is important to note that the number of intervals at each site (n_i) depends on the number of lanes (i.e., n_i = number of lanes × 1,440/15). Before comparing the speed data of the *before* period to those of the *program* period, the relationship between speed and traffic flow in is examined.

3.2.2 The Speed-Flow Relationship and Level of Service

There are three commonly referenced macroscopic parameters to describe a traffic stream: speed, density, and rate of flow. They are related as follows:

$$V = S \times D$$

- V= Rate of flow (vehicle/hour/lane)
- S= Space mean speed (mph)
- D= Density (vehicles/mile/lane)

Density and speed are parameters for a specific section, while rate of flow is a parameter for a point. There have been a number of studies to reveal the shape of these relationships, but the relationship depends upon prevailing conditions. Figure 11 shows a recently depicted speed-flow relationship (Transportation Research Board, 2000), which is a typical of traffic patterns on uninterrupted flow facilities.

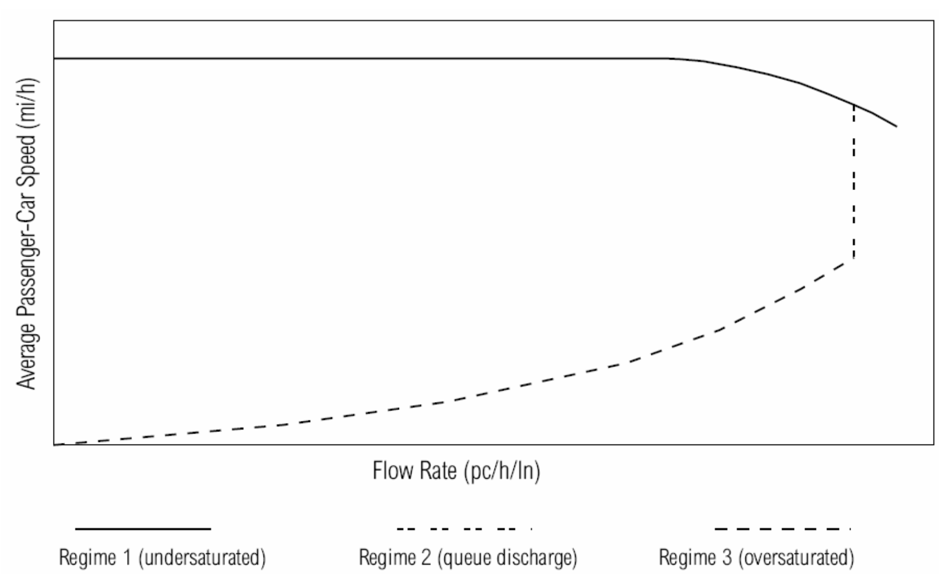


Figure 11: Speed-flow curve [Source: HCM 2000]

The three identified regimes of the speed-flow curve in Figure 11 can be described as follows (Roess *et al.*, 2004):

- Regime 1: This regime is in the stable (or undersaturated) condition where drivers can maintain a high speed that is unaffected by upstream or downstream conditions. The flat portion of the curves usually defines free-flow speed. Speed begins to decline in response to increasing flow rates. However, the total decline in speed from free-flow speed to the speed at capacity is often 5mi/h or less.

- The inflection point, which indicates the flow rate at which speed begins to decline, is often in the range of 1,500–1,700 pc/h/ln (passenger cars per hour per lane).
- Note that the path from free-flow speed to capacity is often associated with a relatively small increase in the flow rate.

- Regime 2: This portion of the curve is called "queue discharge." Once demand exceeds capacity, a breakdown occurs and a queue propagates upstream of the point of breakdown. Once the queue forms, flow is restricted to what is discharged from the front of the queue. The variable speed for Regime 3 reflects the fact that vehicles discharge from a queue into an uncongested downstream segment.
- Regime 3: This portion of the curve reflects the unstable operating conditions within the queue, upstream of the breakdown, in which traffic flow is influenced by the effects of a downstream condition. Traffic flow in the regime can vary over a broad range of flows and speeds depending on the congestion severity.

  Unlike a stable flow condition, queue discharge and congested flow have not been extensively studied. Thus, the speed-flow curve for the two regimes should be considered conceptual at best. Further research is needed to better define flow in these two regimes.

The modern speed-flow curve implies that the effects of traffic flow on speed are different across regimes. Since focus in this study is on the speed distribution in regime 1 rather than that in regimes 2 or 3, it is necessary to determine and classify regime 1. The concept of the level of service (LOS) is applied to identify regime 1 (undersaturated).

In general, LOS is characterized using three performance measures: density in terms of passenger cars per mile per lane, speed in terms of mean passenger-car speed, and the volume-to-capacity (v/c) ratio. Each of these measures is an indication of how well traffic flow is being accommodated by the freeway. For a basic freeway section, the LOS is defined by reasonable ranges using the 3 critical flow variables: speed, density, and flow rate. Figure 12 shows the speed-flow curves that depend on free-flow speeds. All curves have the same speed-flow relationship for regimes 1 and 2 as illustrated in Figure 11, but each curve has a different intercept that depends on free-flow speed. In addition, each LOS has the minimum or maximum values for the 3 parameters. The minimum or maximum values for the parameters are summarized in Table 17, which can be used to determine LOS.

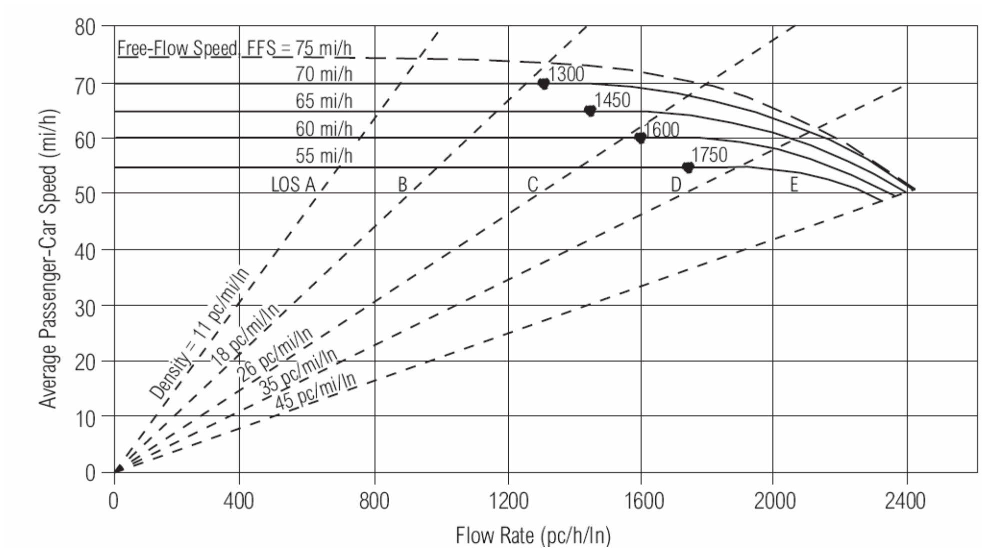


Figure 12: Speed-flow curves and LOS on a basic freeway segment [Source: HCM 2000]

Table 17: LOS criteria for basic freeway sections

Criteria	LOS				
	A	B	C	D	E
FFS = 75 mi/h					
Maximum density (pc/mi/ln)	11	18	26	35	45
Minimum speed (mi/h)	75.0	74.8	70.6	62.2	53.3
Maximum v/c	0.34	0.56	0.76	0.90	1.00
Maximum service flow rate (pc/h/ln)	820	1350	1830	2170	2400
FFS = 70 mi/h					
Maximum density (pc/mi/ln)	11	18	26	35	45
Minimum speed (mi/h)	70.0	70.0	68.2	61.5	53.3
Maximum v/c	0.32	0.53	0.74	0.90	1.00
Maximum service flow rate (pc/h/ln)	770	1260	1770	2150	2400
FFS = 65 mi/h					
Maximum density (pc/mi/ln)	11	18	26	35	45
Minimum speed (mi/h)	65.0	65.0	64.6	59.7	52.2
Maximum v/c	0.30	0.50	0.71	0.89	1.00
Maximum service flow rate (pc/h/ln)	710	1170	1680	2090	2350
FFS = 60 mi/h					
Maximum density (pc/mi/ln)	11	18	26	35	45
Minimum speed (mi/h)	60.0	60.0	60.0	57.6	51.1
Maximum v/c	0.29	0.47	0.68	0.88	1.00
Maximum service flow rate (pc/h/ln)	660	1080	1560	2020	2300
FFS = 55 mi/h					
Maximum density (pc/mi/ln)	11	18	26	35	45
Minimum speed (mi/h)	55.0	55.0	55.0	54.7	50.0
Maximum v/c	0.27	0.44	0.64	0.85	1.00
Maximum service flow rate (pc/h/ln)	600	990	1430	1910	2250

The general definitions of LOS are as follows (Transportation Research Board, 2000):

- LOS A describes free-flow operations. Free-flow speeds prevail. Vehicles are almost completely unimpeded in their ability to maneuver within the traffic stream. The effects of incidents or point breakdowns are easily absorbed at this level.
- LOS B represents reasonably free flow, and free-flow speeds are maintained. The ability to maneuver within the traffic stream is only slightly restricted, and the general level of physical and psychological comfort provided to drivers is still high. The effects of minor incidents and point breakdowns are still easily absorbed.
- LOS C provides for flow with speeds at or near the FFS of the freeway. Freedom to maneuver within the traffic stream is noticeably restricted, and lane changes require more care and vigilance on the part of the driver. Minor incidents may still be absorbed, but the local deterioration in service will be substantial. Queues may be expected to form behind any significant blockage.
- LOS D is the level at which speeds begin to decline slightly with increasing flows and density begins to increase somewhat more quickly. Freedom to maneuver within the traffic stream is more noticeably limited, and the driver experiences reduced physical and psychological comfort levels. Even minor incidents can be expected to create queuing, because the traffic stream has little space to absorb disruptions.
- LOS E describes operation at capacity. Operations at this level are volatile, because there are virtually no usable gaps in the traffic stream. Vehicles are closely spaced, leaving little room to maneuver within the traffic stream at speeds that still exceed 49 mi/h. Any disruption of the traffic stream, such as vehicles entering from a ramp or a vehicle changing lanes, can establish a disruption wave that propagates throughout the upstream traffic flow. At capacity, the traffic stream has no ability to dissipate even the most minor disruption, and any incident can be expected to produce a serious breakdown with extensive queuing. Maneuverability within the traffic stream is extremely limited, and the level of physical and psychological comfort afforded the driver is poor.
- LOS F describes breakdowns in vehicular flow. Such conditions generally exist within queues forming behind breakdown points.

3.2.3 Effect of the SEP on Mean Speeds

In order to control for the measurement date and day of week effects, the traffic volume and speed data obtained from the enforcement zone during the program period were carefully selected from the set of the speed and traffic flow data collected during the program period. Therefore, the speed and traffic flow data during the 3 identical times and days of the program period (Table 15) were selected: 4/13/2006 (Thursday), 4/19/2006 (Wednesday), and 6/27/2006 (Thursday). The descriptive statistics for the speed data during the *before* and *program* periods are summarized in Table 18.

Table 18: Summary statistics for the speed during the before and program periods

Period	Mean	Std.Dev.	Min	Max	N
Before	72.56	5.12	32.9	82	576
Program	63.17	4.42	19	68.33	1709
Total	65.54	6.15	19	82	2285

In order to analyze the effect of the SEP on mean speed, the analysis of covariance (ANCOVA) models were used. Note that the ANCOVA model is essentially the same as the general linear regression model, but the terminology ANCOVA model is consistently used in this analysis because our interest lies in testing whether of not the aggregated factors are significant. We used 6 ANCOVA models to test numerous assumptions. The results of the testing are summarized in Table 19.

The measurement date effects were tested by adding the variable *Date* and the interaction between *Date* and *Period* in Models I and II. The ANCOVA model results show that the measurement date effect is not significant, indicating that the speed and traffic flow data are independent random samples. In Model III, the interaction between *Period* and the covariate *Traffic Flow* are tested. The result shows that there is no significant evidence supporting an interaction between the variables. Figure 13 also shows that the interaction is not significant, but the mean speed has different intercepts for the 2 periods (the intercept for the before period is greater than that for the program period). However, the linear relationship does not hold because the data include the traffic volume and speed for regime 3 as well as regime 1 and 2, which were discussed in the previous section (see "The Speed-Flow Relationship and Level of Service" on page 39). Therefore, it is necessary to exclude the speed data from regime 3 in order to precisely estimate the effect of the SEP on mean speed.

In order to determine the borderline between regime 2 and regime 3, we used the concept of the LOS discussed in the previous section. The 70 mph speed was used as the free flow speed for determining the LOS, and the LOS A, B, C, and D are selected based on the given criteria in Table 17 (i.e., speed for LOS D: 61.5 mph). Consequently, the sample size was reduced from 1,560 intervals to 1,390 intervals, and the ANCOVA model was re-estimated. The result shown in Table 19 (Model V) indicates that the covariate traffic flow remains significant with the factor of interest *Period.*

Table 19: The ANCOVA model results

Model	Source	DF	Seq SS	Adj SS	Adj MS	F	P	Adj R^2
Model I	Traffic Flow	1	5950	6200	6200	432.21	<.0001	0.6076
	Period	1	28698.6	28688.2	28688.2	1999.87	<.0001	
	Date	2	35.8	35.8	17.9	1.25	0.287	
	Error	1555	22306.5	22306.5	14.3			
	Total	1559	56990.9					
Model II	Traffic Flow	1	5950	6149.5	6149.5	428.91	<.0001	0.6078
	Period	1	28698.6	3867.6	3867.6	269.75	<.0001	
	Date	2	35.8	61.3	30.6	2.14	0.118	
	Period* Date	2	40.4	40.4	20.2	1.41	0.245	
	Error	1553	22266.1	22266.1	14.3			
	Total	1559	56990.9					
Model III	Traffic Flow	1	5950	4576	4576	318.7	<.0001	0.6073
	Period	1	28699	7962	7962	554.57	<.0001	
	Traffic Flow*Period	1	3	3	3	0.21	0.648	
	Error	1556	22339	22339	14			
	Total	1559	56991					
Model IV	Traffic Flow	1	5950	6271	6271	436.98	<.0001	0.6075
	Period	1	28699	28699	28699	1999.96	<.0001	
	Error	1557	22342	22342	14			
	Total	1559	56991					
Model V	Traffic Flow	1	688	1829	1829	475.85	<.0001	0.8222
	Period	1	24011	24011	24011	6246.98	<.0001	
	Error	1387	5331	5331	4			
	Total	1389	30030					
Model VI	Traffic Flow	1	688.5	1962.2	1962.2	526.94	<.0001	0.8278
	Period	1	24010.6	8634.5	8634.5	2318.75	<.0001	
	Traffic Flow*Period	1	169.9	169.9	169.9	45.62	<.0001	
	Error	1386	5161.1	5161.1	3.7			
	Total	1389	30030					

In addition, the interaction between *Period* and the covariate *Traffic Flow* is significant as shown in Table 19 (see the results for Model VI) and Figure 14, when using the data on regime 1 and 2.

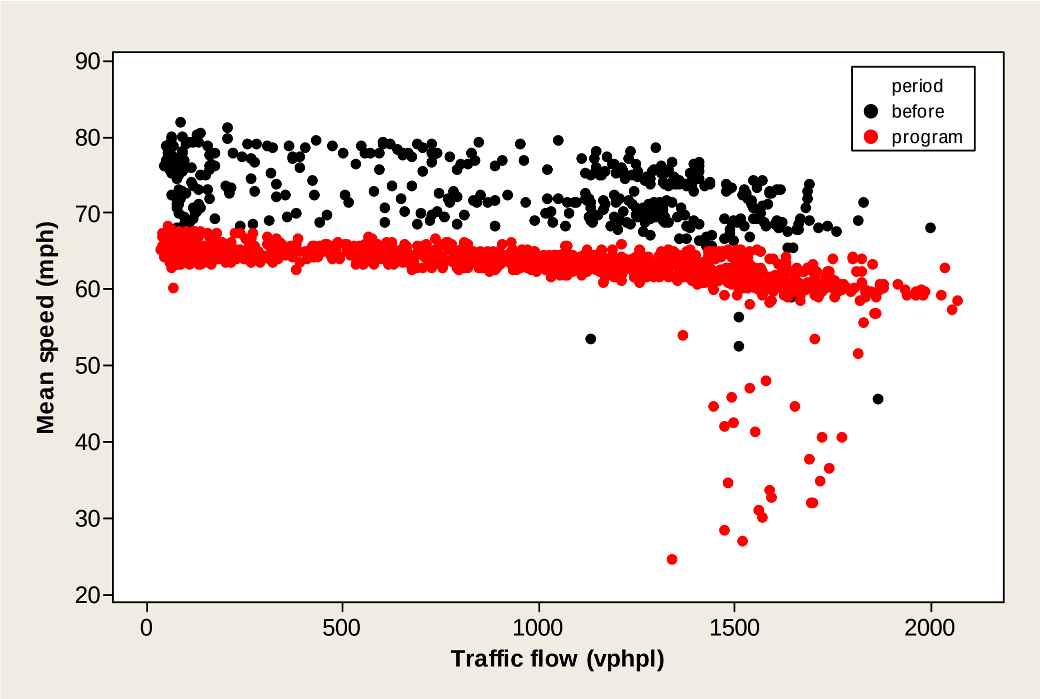


Figure 13: Speed-traffic flow relationship by period (all regimes)

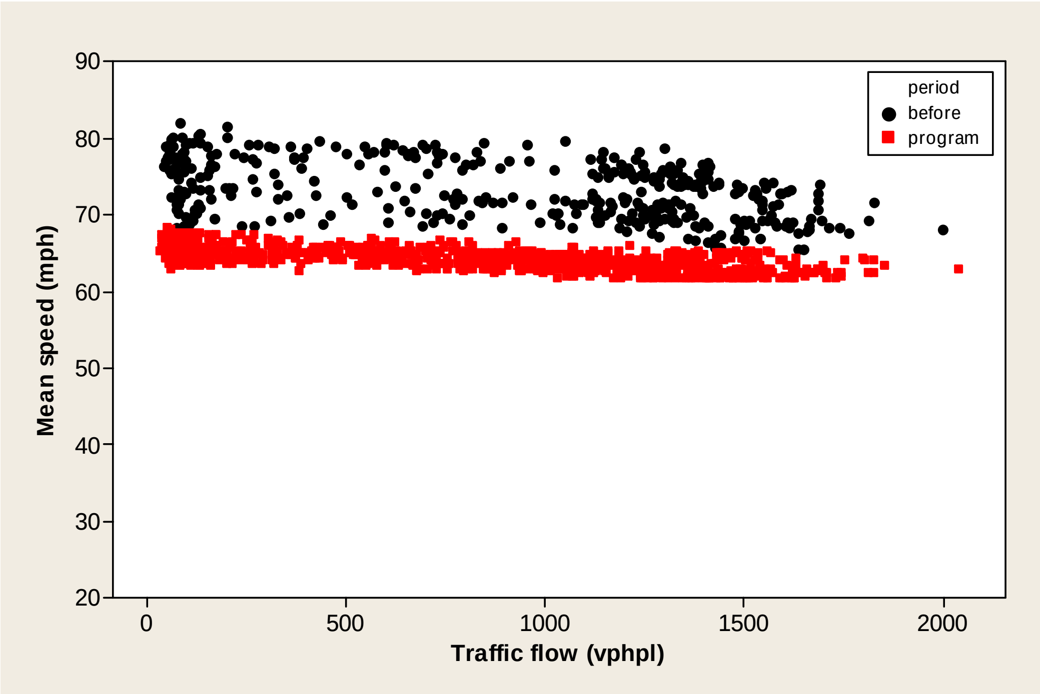


Figure 14: Speed-traffic flow relationship by period (regime 1 and 2)

Since Model VI shows a superior adjusted R^2 and smaller MSE, Model VI was used to estimate the effect of the SEP on mean speed. Table 20 shows the estimated factor level means (mean speeds) and associated statistics, which were derived from Model VI. By using the estimated mean speeds and MES of the Model VI, the difference in the mean speed between the before and program periods was estimated as shown in Table 20.

Table 20: Estimated factor level means and associated statistics

Period	Mean speed	Std.Err.	P-value	95% CIs	
				Lower	Upper
Before period (1)	73.57	0.0995	<.0001	73.377	73.767
Program period (2)	64.17	0.0611	<.0001	64.045	64.285
Difference	–9.407	0.1168	<.0001	–9.636	–9.178

Again, the percent change is obtained using these estimates. The estimated results reveal that:

- After the demonstration program was implemented, the mean speed decreased by 12.78% (9.4 mph) compared to that of the *before* period.
- The effect of the SEP on the mean speed is estimated to be between 12.48% (9.78 mph reduction) and 13.09% (9.64 mph reduction).
- It is very likely that most of this speed drop is due to compression of speeds of upper decile drivers (drivers with speeds in top 10%) because the speed data on regime 3 were eliminated from this analysis.

3.2.4 Changes in Mean Speed at the Comparison Site

In this subsection, the change in the mean speed at the comparison site during the before and program periods is analyzed. The same approaches employed in the previous subsection are used to analyze the change in the mean speed at the comparison site. Examining the change in mean speed at the comparison sites provides a test to determine if there is evidence of a spillover effect from the SEP on the comparison site. Note that international experience has not revealed significant spillover effects in this regard.

3.2.4.1 Data Description

The comparison site is located on the west side of SR 101 between Northern Ave. and Glendale Ave. (see Figure 15). The traffic volume and mean speed data used in this analysis were collected from October 2005 to September 2006, and the summary statistics for the mean speeds are summarized in Table 21 and Table 22.

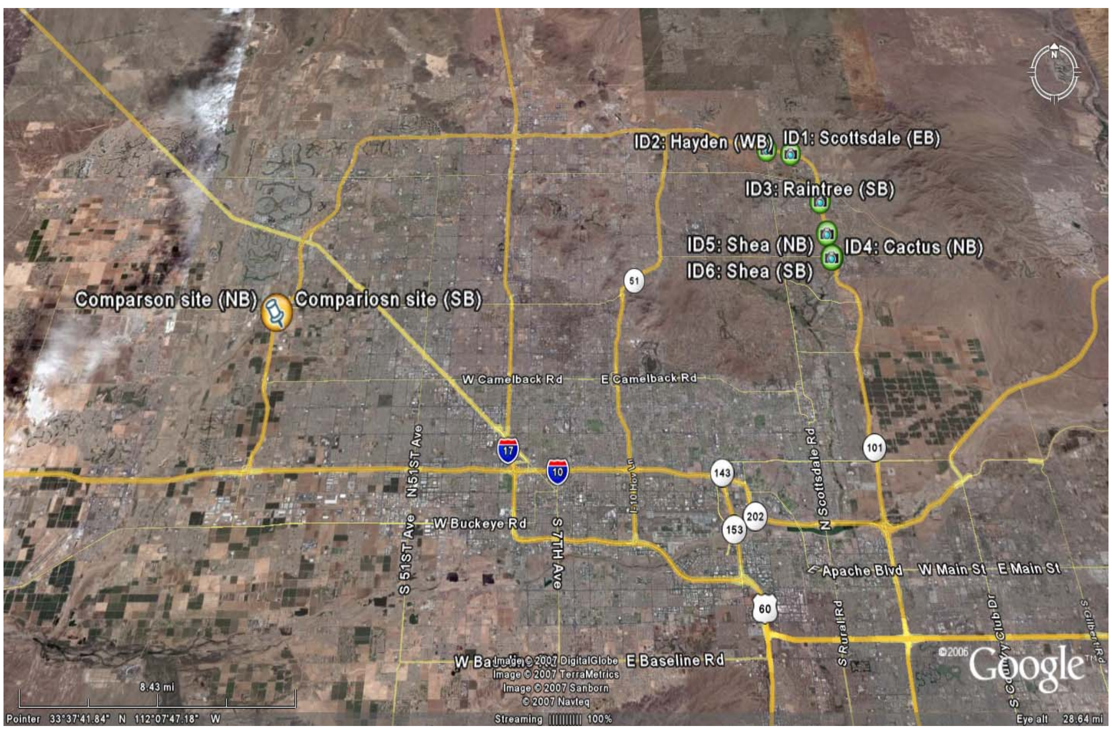


Figure 15: Location of the comparison site

Regardless of the direction, the mean speed fluctuated around 70 mph to 68 mph. The trend in the mean speed by month is shown in Figure 16 and Figure 17, in which LOS C based on the free-flow speed 70 mph was used to eliminate the mean speeds in regime 3. After eliminating the speed data in regime 3, the variance of the mean speeds is reduced, and the mean speeds are not remarkably different from those of all regimes. In the next subsection, the statistical difference in the mean speeds during the before and program periods is analyzed.

Table 21: Summary statistics for the mean speed at the comparison site for 9 months (all regimes)

Period	Month	North bound					South bound					All directions				
		Mean	Std. dev	Min	Max	N	Mean	Std. dev	Min	Max	N	Mean	Std. dev	Min	Max	N
Before	Oct-05	68.99	1.78	47.33	72.10	504	69.36	3.40	54.68	73.57	480	69.17	2.70	47.33	73.57	984
Warning	Feb-06	68.80	1.89	45.03	72.37	336	66.95	5.50	45.00	71.72	336	67.87	4.21	45.00	72.37	672
Program	Mar-06	67.82	3.09	45.06	70.91	336	68.26	1.40	62.41	71.18	336	68.04	2.41	45.06	71.18	672
	Apr-06	68.91	1.74	47.53	71.59	336	69.31	1.17	65.56	73.22	336	69.11	1.49	47.53	73.22	672
	May-06	68.02	0.91	63.70	70.79	360	67.65	3.97	45.00	71.86	360	67.84	2.88	45.00	71.86	720
	Jun-06	68.66	1.05	61.11	71.26	336	68.38	2.46	55.50	71.33	336	68.52	1.89	55.50	71.33	672
	Jul-06	68.77	1.33	53.70	71.19	336	67.16	2.67	45.19	70.14	336	67.96	2.26	45.19	71.19	672
	Aug-06	68.62	1.47	54.63	71.08	360	67.35	2.13	51.23	70.27	360	67.98	1.94	51.23	71.08	720
	Sep-06	68.96	1.55	47.33	71.66	336	67.89	1.78	57.59	71.63	336	68.43	1.75	47.33	71.66	672
Total		68.63	1.79	45.03	72.37	3240	68.09	3.15	45.00	73.57	3216	68.36	2.57	45.00	73.57	6456

Table 22: Summary statistics for the mean speed at the comparison site for 9 months (regime 1 and 2)

Period	Month	North bound					South bound					All directions				
		Mean	Std. dev	Min	Max	N	Mean	Std. dev	Min	Max	N	Mean	Std. dev	Min	Max	N
Before	Oct-05	69.43	0.76	68.21	72.10	416	70.17	1.83	61.58	73.57	445	69.81	1.47	61.58	73.57	861
Warning	Feb-06	69.35	0.73	68.21	72.37	270	69.36	0.77	68.23	71.72	199	69.35	0.74	68.21	72.37	469
Program	Mar-06	69.10	0.64	68.23	70.91	203	68.99	0.70	68.20	71.18	211	69.04	0.67	68.20	71.18	414
	Apr-06	69.43	0.82	68.21	71.59	261	69.63	0.98	68.21	73.22	282	69.53	0.91	68.21	73.22	543
	May-06	68.90	0.61	68.21	70.79	139	69.50	0.95	68.20	71.86	182	69.24	0.87	68.20	71.86	321
	Jun-06	69.15	0.71	68.21	71.26	232	69.51	0.77	68.23	71.33	234	69.33	0.76	68.21	71.33	466
	Jul-06	69.30	0.74	68.22	71.19	242	68.94	0.53	68.21	70.14	126	69.18	0.70	68.21	71.19	368
	Aug-06	69.04	0.60	68.22	71.08	286	69.02	0.57	68.24	70.27	103	69.04	0.59	68.22	71.08	389
	Sep-06	69.32	0.73	68.21	71.66	276	69.05	0.66	68.20	71.63	159	69.23	0.71	68.20	71.66	435
Total		69.26	0.73	68.21	72.37	2325	69.50	1.19	61.58	73.57	1941	69.37	0.98	61.58	73.57	4266

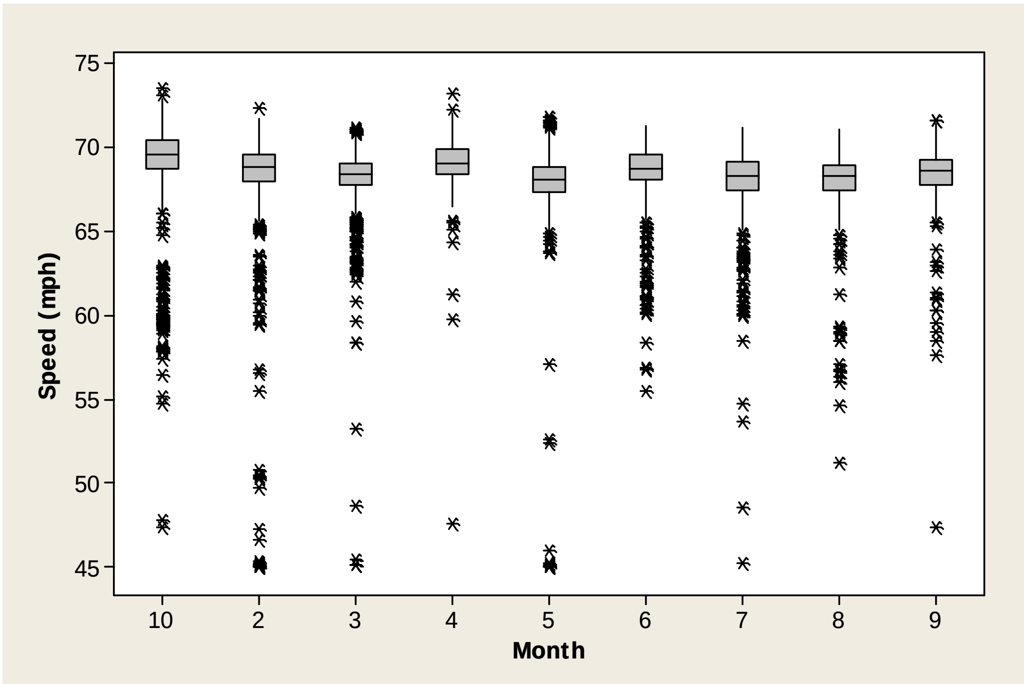


Figure 16: Box plot of the mean speed by month (all regimes)

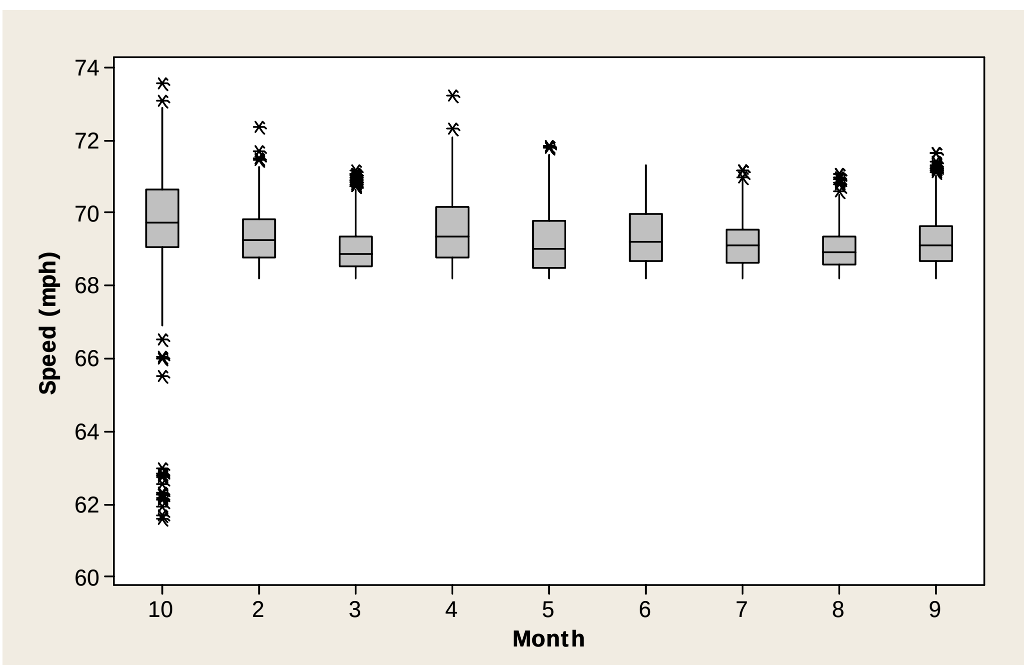


Figure 17: Box plot of the mean speed by month (regime 1 and 2)

3.2.4.2 Differences in the Mean Speeds during the 3 Periods

As with the analysis for the changes in mean speeds at the SEP site, the difference in mean speeds at the comparison zone by time period is analyzed using the data collected from flow regimes 1 and 2. Again, ANCOVA models were applied to reveal whether or not the mean speeds are different during the 3 periods, and the results of the ANCOVA models are summarized in Table 23.

In the Northbound direction there is no significant difference between the mean speeds during the 3 periods (Model 1). However, the effect of the period on the mean speeds is significant in Model II and III, indicating that the mean speeds during the 3 periods are different.

Table 23: Results of the ANCOVA models

Model	Source	DF	Seq SS	Adj SS	Adj MS	F	P	Adj R^2
Model I (North Bound)	Traffic Flow	1	0.33	0.33	0.33	0.62	0.432	0.016
	Period	2	19.28	0.28	0.14	0.27	0.767	
	Traffic Flow*Period	2	3.23	3.23	1.61	3.05	0.048	
	Error	2319	1227.41	1227.41	0.53			
	Total	2324	1250.26					
Model II (South Bound)	Traffic Flow	1	24.83	37.68	37.68	29.65	<.0001	0.11
	Period	2	274.47	25.57	12.79	10.06	<.0001	
	Traffic Flow*Period	2	11.89	11.89	5.94	4.68	0.009	
	Error	1935	2459.01	2459.01	1.27			
	Total	1940	2770.19					
Model III (All directions)	Traffic Flow	1	15.45	24.70	24.70	27.43	<.0001	0.06
	Period	2	217.15	12.70	6.35	7.05	0.001	
	Traffic Flow*Period	2	16.68	16.68	8.34	9.26	<.0001	
	Error	4260	3836.00	3836.00	0.90			
	Total	4265	4085.29					

Since the results do not indicate how the mean speeds at the comparison sites are different during the 3 periods, the Tukey's simultaneous comparison analysis was conducted for all ANCOVA models. The simultaneous comparison results summarized in Table 24 indicate that the difference in the mean speeds for the *north bound site* between the *before* and *warning* periods is 0, while the differences in the mean speed for other pairs are not 0 (the mean speeds during the *before* and *warning* periods are slightly greater than the mean speed during the *program* period: the differences are 0.153 mph or 0.221 mph).

Although the mean speeds at the *south bound site* during the *before* and *warning* periods are also slightly greater than the mean speed during the *program* period, the difference in the mean speeds between the *warning* and *program* periods is insignificant. Therefore, there is not a decreasing speed trend in the mean speeds across the 3 time periods at the comparison site. As a result, there is no evidence for a spillover effect of the SEP on the comparison site, and the comparison site meets one of the requirements of a suitable site.

When aggregating the mean speeds from the 2 directions, all differences in the mean speeds between periods are statistically significant. Although the differences in the mean speeds are significant, the differences (0.125 mph to 0.575 mph) were substantially smaller than those within the enforcement zone (9.18 mph to 9.64 mph). In addition, it is necessary to note that the differences in speed might be attributed to unobserved effects such as a month effect although 2 factors and interaction terms were included in the ANCOVA model to reduce the variance of the error from such effects.

Table 24: Test results of the differences in the mean speed at the comparison sites

Direction	Pair	Difference (mph)	P-value	95% CIs	
				Lower	Upper
North bound	"Before"–"Warning"	*0.068*	0.4693	-0.068	0.203
	"Before"–"Program"	0.221	<0.0001	0.127	0.315
	"Warning"–"Program"	0.153	0.0049	0.039	0.268
South bound	"Before"–"Warning"	0.845	<0.0001	0.618	1.072
	"Before"–"Program"	0.926	<0.0001	0.780	1.073
	"Warning"–"Program"	*0.081*	0.611	-0.120	0.283
All directions	"Before"–"Warning"	0.450	<0.0001	0.321	0.579
	"Before"–"Program"	0.575	<0.0001	0.489	0.661
	"Warning"–"Program"	0.125	0.0239	0.013	0.237

Note: The italic differences are insignificant at α=0.05.

Chapter 4 Effects of the SEP on Traffic Safety

In this chapter, the effects of the SEP on traffic safety are comprehensively analyzed. Target crashes are first carefully determined by using the detection trend in terms of time of day. The evaluation methodologies used in the study are described in detail, and the results of each methodology are presented. In addition, the economic benefits obtained from the demonstration program are quantified using Arizona-specific crash costs.

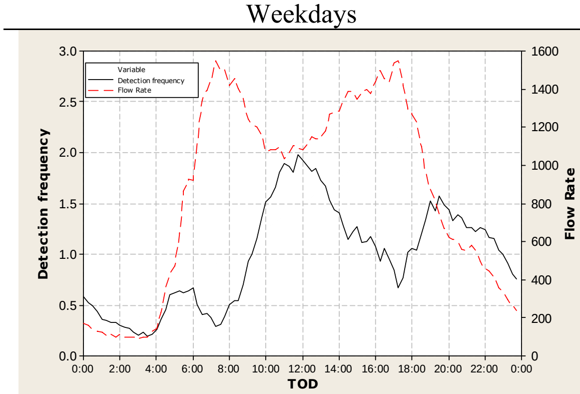
4.1 Preliminaries: Target Crashes and Data Description

4.1.1 Determining Target Crashes

Before estimating the impacts of the SEP on traffic safety, it is necessary to define which crashes are materially affected by the speed enforcement cameras—referred to as "target" crashes. Since the crashes occurring during the peak travel periods are unlikely to be significantly affected by the photo enforcement cameras, target crashes are defined as crashes that occurred during the off-peak periods.

In order to define the off-peak periods, the time of day (TOD) was used in this analysis because traffic flow data were not available for all data pertaining to the *before* period. Figure 18 shows the detection frequencies by TOD, in which the detection frequency is the average number of detections per 15-minute interval at the enforcement sites for the program period. The detection frequencies by TOD indicate that detection frequencies decrease during peak hours for weekdays, while they are almost proportional to traffic flow for weekends and holidays. Therefore, TOD is generally related to speeding behaviors on weekdays.

Weekdays



Weekends and Holidays

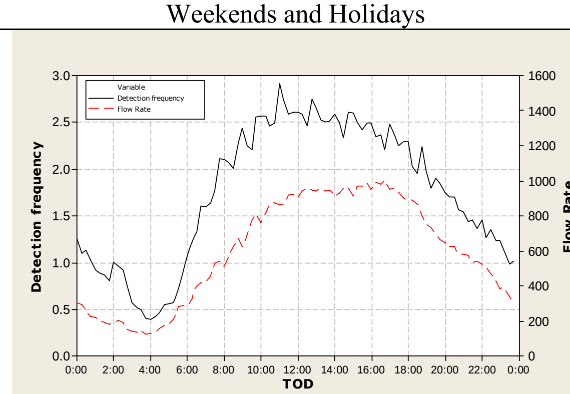


Figure 18: Detection frequencies by TOD

In addition, the relationships between TOD and detection rates shown in Figure 19 indicate that the detections could occur for weekends and holidays regardless of traffic flow, while the detections are related to the changes in traffic flow, in which the detection rate is the ratio of detection frequency to the average traffic volume per 15-minute interval at the enforcement sites for the program period. For example, the detection rates during peak hours for weekdays are remarkably low—less than 0.25% between 6:00 AM and 9:00 AM.

Weekdays	Weekends and Holidays

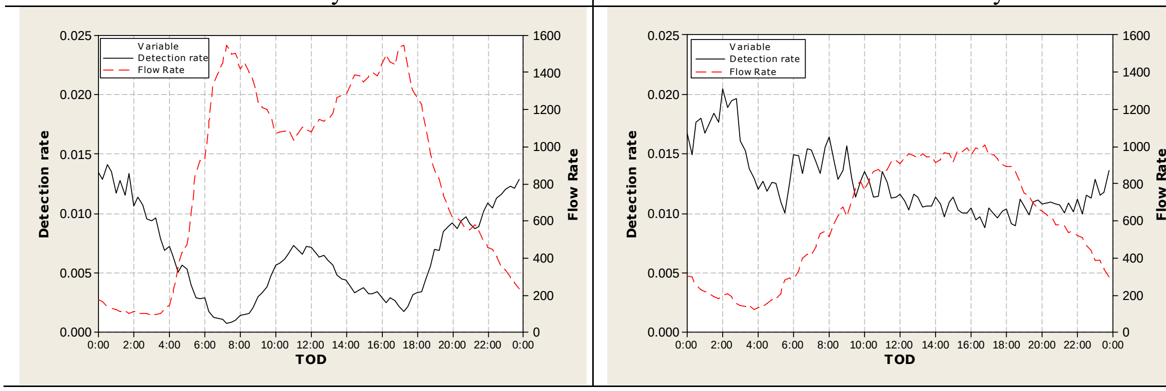


Figure 19: Detection rates by TOD

Since the detection trends by TOD suggest that TOD can be used to identify traffic flow regimes, two traffic flow regimes (peak and off-peak periods) are defined by using TOD.

- Peak periods (6 hours)
  - 06:00 AM — 09:00 AM
  - 16:00 PM — 19:00 PM
- Off–peak periods
  - The remaining 18 hours for weekdays
  - 24 hours for weekends and holidays

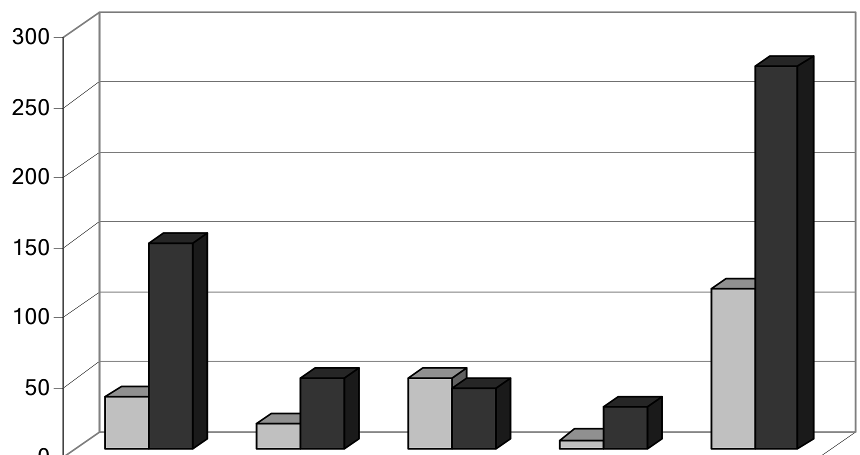
Consequently, the target crashes in this analysis are the crashes that occurred within the enforcement zone (MP 34.51 – MP 41.06: 6.5 miles) during the off-peak travel periods defined by TOD (because of the limited expected influence of the cameras on slow moving peak period traffic). Note that the target crashes are "mainline" crashes classified by ADOT, excluding crashes that occurred on SR 101 ramps and frontage roads. In the next subsection, the characteristics of the target crashes are discussed in detail.

4.1.2 Crash Data Description

In this subsection, the characteristics of the target crashes determined in the previous subsection are discussed. The durations of the target crash data are summarized below:

- Crash data during the *before* period
  - Duration: 2/22/2006 – 8/31/2006 (2001 through 2005)
- Crash data during the *program* period
  - Duration: 2/22/2006 – 8/31/2006 (191 days)

Note that the SEP ended October 22, 2006, but the current analysis is based on the limited crash data. Figure 20 shows the number of crashes that occurred within the enforcement zone during the *before* period. It contains target crashes as well as the crashes that occurred during the peak periods. Although the average number of crashes during the 2 periods (peak and off-peak periods) cannot be compared directly, three crash types are most frequent: single-vehicle, side-swipe (same), and rear-end crashes. Therefore, the remaining crash types such as angle, left-turn, side-swipe (opposite), head-on, and other crashes are aggregated as “other” in this analysis.



	Single-vehicle	Side-swipe (same)	Rear-end	Other	Total
Peak	38	19	51	7	115
Off-peak	148	51	44	31	274

Figure 20: Number of crashes that occurred at the enforcement zone during the before period

Figure 21 and Figure 22 show the percentage of the peak or off-peak crashes by crash type, which occurred during the *before* period. The most frequent crash type was single-vehicle crashes (54%) for the off-peak periods, while rear-end crashes (44%) was most frequent for the peak periods.

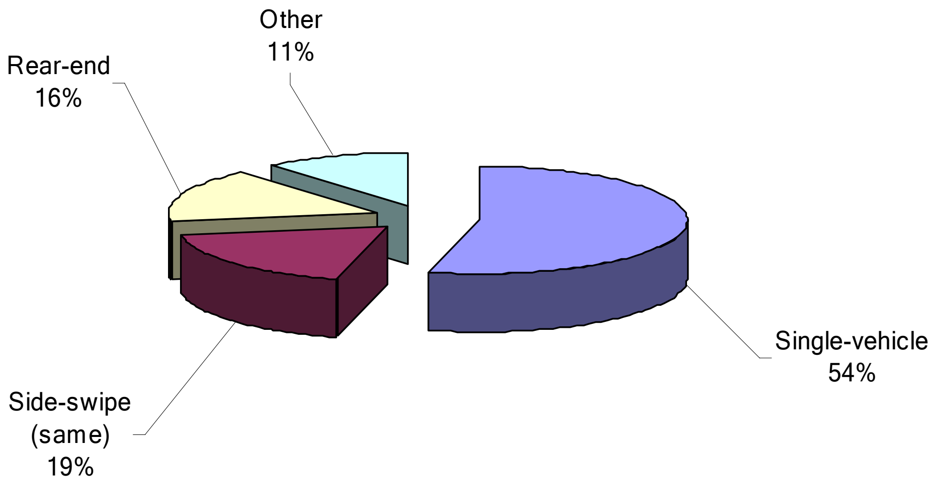


Figure 21: Percentage of off-peak crashes by crash type (before period)

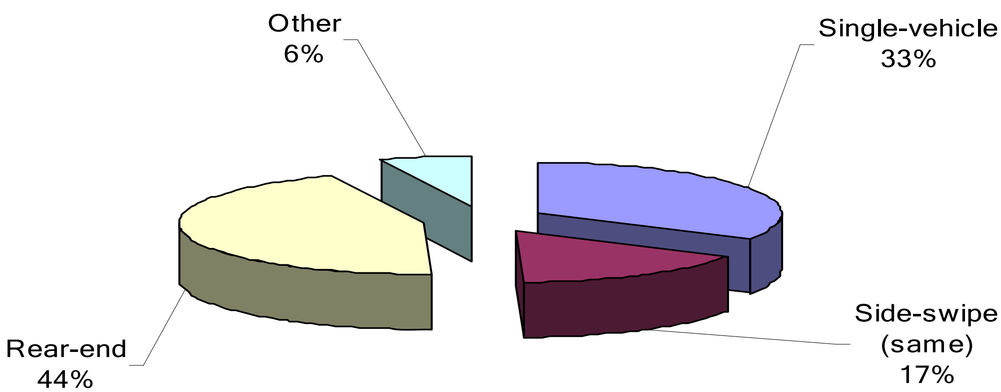


Figure 22: Percentage of peak-period crashes by crash type (before period)

Although it is evident that the characteristics of crashes are different for the 2 periods, the analysis using the target crashes is conservative because the peak period increases over time (the *before* to *program* period), therefore there is increasing constraint on speed over time, or lesser constraint on speed going back in time (the *before* period), resulting in target crashes in the *before* period being eliminated from the analysis (because they occurred during the 'peak' period). Fewer *before* crashes reduces the estimated effectiveness of a countermeasure; therefore this approach is conservative.

4.2 The Four-Step Procedures for Before and After Study

In this section, the basic concepts of the before-and-after (BA) study are described, and the basic 4-step procedure for estimating the effects of SEP is also provided. The analysis approach developed and described here is an expansion and mathematical formalization of the methods described by Hauer (Hauer, 1997; Hauer *et al.*, 2002).

The key objective of the BA study is to estimate the change of safety in the program period as a result of the treatment. The key notations used are:

- π: Expected number of target crashes in the program period if the treatment had not been installed
- λ: Expected number of target crashes in the program period with the treatment in place
- $\delta = \pi - \lambda$: Change in safety due to the treatment
- $\theta = \lambda/\pi$: Index of the effectiveness of the treatment

If either δ is greater than 1 or θ is less than 1, then we conclude that the treatment is effective. The parameters π, λ, δ, and θ are unknown parameters and must be estimated using the available data. There are numerous arduous aspects of estimating these unknown parameters. Generally, the value of λ is being estimated using the observed number of crashes in the after period. It might seem that the observed number of crashes in the before period would be employed to predict the value of π.

Figure 23 illustrates the basic concept of the BA study. As discussed, the key objective of the analysis is to estimate the expected number of crashes in the program period if the SEP had not been implemented. If we do not assume any change from before to program periods, the estimates of the π's are the same as the observed target crash frequency during the before period (i.e., k's). However, it is insufficient to predict the value of π using the observed number of crashes in the before period. Problems arise because there are either potentially many recognizable and unrecognizable factors which may have changed from the before to after periods, or the regression to the mean bias that has resulted from sites being selected based on prior crash histories. Thus, often more rigorous evaluation methodologies are needed to obtain accurate estimates of π, which are described in detail in the following subsection.

Regardless of the corrections made to the BA study, a basic 4-step procedure is used (with modifications) to estimate the safety effect of a treatment. In the next subsections, we provide the 4-step procedure for the simple or naïve BA study approach.

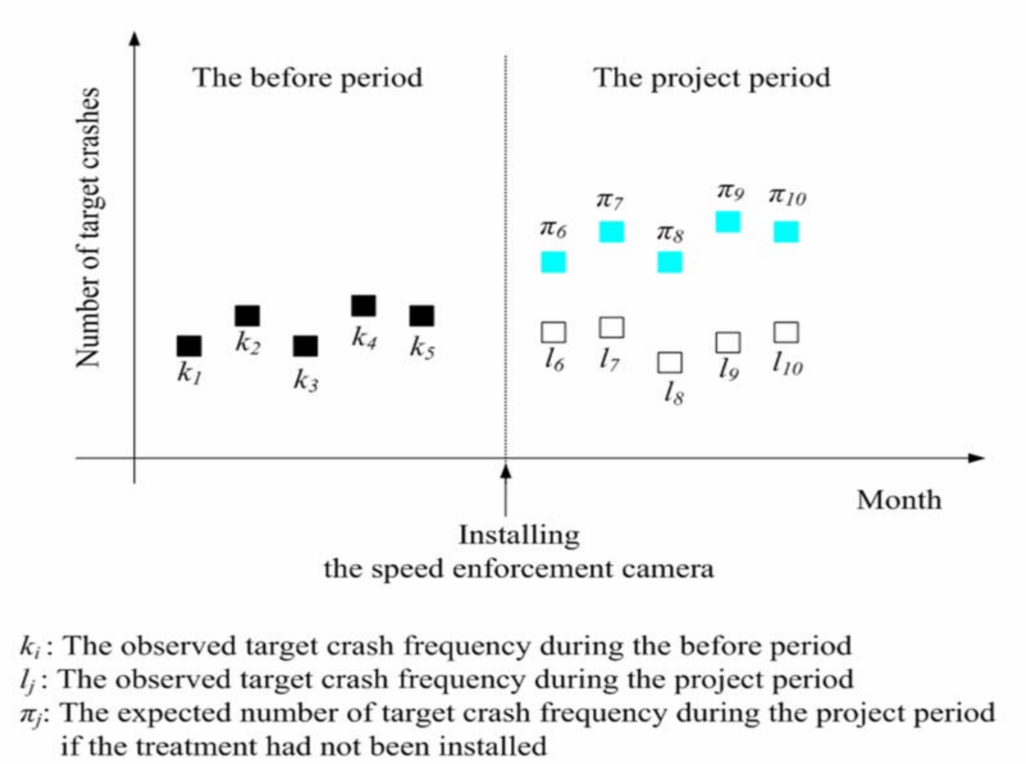


Figure 23: Basic concept of the before-and-after study

Step 1: Estimate λ and predict π

The first step is to estimate λ and π. The estimate of λ is equal to the sum of the observed number of target crashes in the program 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 BA study, these estimates are:

$$\hat{\pi} = \sum_{i=1}^{b} k_i = K \tag{1}$$

and

$$\hat{\lambda} = \sum_{j=1}^{p} l_i = L, \tag{2}$$

where *b* and *p* are the number of durations for the before and program periods respectively, and *k* and *l* are the observed target crash frequencies during the before and program periods.

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.

$$\hat{\sigma}^2[\hat{\lambda}] = \lambda \tag{3}$$

and

$$\hat{\sigma}^2[\hat{\pi}] = \pi. \tag{4}$$

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

Step 3: Estimate δ and θ

The estimates of treatment effectiveness, *δ* and *θ*, can be estimated:

$$\hat{\delta} = \hat{\pi} - \hat{\lambda} = K - L. \tag{5}$$

The estimator of *θ* was obtained by using the well-known delta approximation, because *θ* is a non-linear function of two random variables. Since the applications of the delta method are necessarily brief, the interested reader can refer to two references for a full derivation and justification (Hauer, 1997; Washington and Shin, 2005) and consult two of a variety of references for the delta method (Greene, 2003;Hines *et al.*, 2003).

$$\hat{\theta} \cong \frac{\left(\hat{\lambda}/\hat{\pi}\right)}{\left\{1 + \widehat{Var}[\hat{\pi}]/\hat{\pi}^2\right\}} \tag{6}$$

Equation (6) shows that it is also necessary to estimate the variance of $\hat{\pi}$ in order to estimate the index of the effectiveness *θ*. The variance for $\hat{\pi}$ can be estimated by using the assumption that the number of target crashes is Poisson distributed.

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

The final step is to estimate the variance of the effects obtained by using four different methods, which can be used to approximate the "level of confidence" of the results. Equation (7) shows the unbiased estimators for the variances of $\hat{\delta}$ and $\hat{\theta}$, in which the variance of $\hat{\theta}$ is also obtained by using the delta method (Hauer, 1997; Washington and Shin, 2005).

$$\widehat{Var}[\hat{\delta}]=\hat{\pi}+\hat{\lambda};\ \ \widehat{Var}[\hat{\theta}]\cong\frac{\hat{\theta}^2\cdot\left(\frac{\widehat{Var}[\hat{\lambda}]}{\hat{\lambda}^2}+\frac{\widehat{Var}[\hat{\pi}]}{\hat{\pi}^2}\right)}{\left(1+\frac{\widehat{Var}[\hat{\pi}]}{\hat{\pi}^2}\right)^2}. \tag{7}$$

Table 25 shows the goal and formulas for each step in simple BA study 4 step process.

Table 25: The 4-step procedure for simple before-and-after study

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

Correcting for Traffic Volume Differences

The four-step BA procedure can be modified in many ways to account for corrections needed across observation periods. Examples are the duration of the observation period, the number of wet pavement days, or traffic volumes. The only correction we make in this current analysis is for increases in traffic volumes over the demonstration site. At this stage some assumptions needed to be made regarding traffic volume increases from 2005 to 2006. Conservatively, it is estimated that traffic volumes in the section (off-peak) increased by

15% from 2005 to 2006 on average. At the same section of the 101, from 2004 to 2005 traffic volumes increased on average 16%, and increased by 26% from 2003 to 2004. If and when more current traffic volumes for 2006 become available the real increase will be used instead of the assumed 15%. Making this assumption, traffic volumes at 6 locations within the 101 demonstration site are used to compute average correction factors over the site, corrections for increases in traffic exposure over time are incorporated into the BA analysis results. The traffic correction factors, r(tf) for the five years of the *before* period are shown in Table 26.

Table 26: Observed Traffic Volumes (AADT) in Scottsdale 101 Section: 2001 through 2005

Traffic Volume Count Station	2001	2002	2003	2004	2005	2006*
Exit 34 Scottsdale Rd	65,000	67,600	69,400	100,000	142,000	163300
Exit 36 Princess Dr	-	-	80,000	103,000	124,000	142600
Exit 37 Frank Lloyd Wright Blvd	85,000	88,400	90,700	105,000	123,000	141450
Exit 39 Raintree Dr	81,000	84,200	86,400	110,000	115,000	132250
Exit 40 Cactus Rd	90,000	93,600	96,000	118,000	123,000	141450
Exit 41 Shea Blvd	90,000	93,600	96,000	119,000	131,000	150650
Correction Factor, r(tf)	2.12	2.04	1.68	1.33	1.15	1.00

* 2006 volumes estimated assuming a conservative growth of 15%

Correction for exposure to risk, or traffic, is essential to account for the increased number of opportunities for conflict and interaction on a roadway. The correction factors are used to inflate the number of observed crashes in prior years to account for the reduced exposure. For example, crashes that occurred in 2001 are increased by a factor of 2.12 in order to make a meaningful comparison with crashes that occurred in 2006 (since exposure increased by this factor over that same time period). In the simple BA analysis approach, this correction simply modifies the estimate of what would have been the crash counts to $\hat{\pi} = Kr_{(tf)}$. In the case of multiple years, it becomes $\hat{\pi} = \sum_{i=2001}^{2005} K_i r_{(tf)i}$, where crashes are summed over the period 2001 to 2005 using the corrections shown in Table 26.

4.3 The Simple or Naïve Before After Study

The first analysis method is the simple BA study. This approach is based on the following assumptions:

- Traffic volume, roadway geometry, road user behavior, weather, and many other factors have not significantly changed from the *before* to the *program* period.
- There are no treatments or improvements other than the installation of the speed enforcement cameras during the *program* period.
- The probability that crashes are reported is the same in both periods, and the reporting threshold has not changed.

These assumptions may be questionable, but it serves as a starting point for the analysis and provides results that may serve as a baseline for comparison.

As previously discussed, the predicted value of π is simply equal to the average observed number of crashes in the *before* period in the simple before and after study approach. Table 27 shows the estimated values for π, λ, δ, and θ as well as the estimated standard deviation for δ and θ of 4 collision types: single-vehicle, side-swipe (same), rear-end, and other crashes. In addition, the estimates are provided for 3 categories: total crashes, property damage only (PDO) crashes, and total injuries.

Table 27: Simple before and after study results

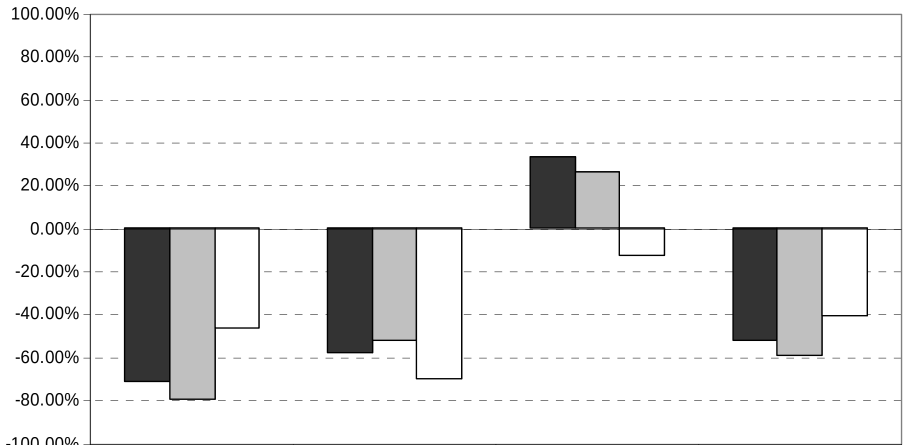
	Collision Type	Crash Estimates		Delta (δ)		Theta (θ)	
		Phi	Lambda	Estimate	Std.Dev	Estimate	Std.Dev
Total Crashes	Single Vehicle	47.47	14	**33.47**	7.84	**0.29**	0.16
	Side-swipe (same)	15.61	7	**8.61**	4.75	**0.42**	0.28
	Rear-end	13.26	19	-5.74	5.68	1.33	0.38
	Other	9.93	2	**7.93**	3.45	**0.18**	0.30
	Total	86.27	42	**44.27**	11.33	**0.48**	0.13
PDO Crashes	Single Vehicle	37.91	8	**29.91**	6.78	**0.21**	0.17
	Side-swipe (same)	11.51	6	**5.51**	4.18	**0.48**	0.32
	Rear-end	8.51	12	-3.49	4.53	1.26	0.45
	Other	6.96	1	**5.96**	2.82	**0.13**	0.33
	Total	64.90	27	**37.90**	9.59	**0.41**	0.14
Total Injuries	Single Vehicle	11.98	7	**4.98**	4.36	**0.54**	0.32
	Side-swipe (same)	5.73	2	**3.73**	2.78	**0.30**	0.38
	Rear-end	10.44	10	**0.44**	4.52	**0.87**	0.38
	Other	4.38	1	**3.38**	2.32	**0.19**	0.39
	Total	32.52	20	**12.52**	7.25	**0.60**	0.21

* Bold numbers indicate crash reduction.

Figure 24 illustrates the percent changes in target crash for each collision type and category, in which the percent changes are $(\hat{\theta} - 1) \times 100$. Therefore, the negative values indicate the crash reduction, while the positive values indicate the increase in crashes. For example, the percent change for total single-vehicle crash frequency (–71.12%) indicates that the total single-vehicle crash frequency was reduced by 71%, while the percent change for total injuries from rear-end crashes (-12.57%) indicates that the total injuries from rear-end crashes decreased by 13% under the assumptions of the simple BA study.

Under the assumptions for the simple BA study, the results suggest that:

- Total target crash frequency was reduced by 52%. Total PDO crashes and total injuries were also reduced by 59% and 40% respectively.
- Total crashes, PDO crashes, and total injuries of single-vehicle and side-swipe (same) crashes were reduced from (52% to 79%).
- Total and PDO crashes of rear-end crashes increased (33% to 26%), while the injuries from rear-ends decreased (12.6%).



	Single Vehicle	Side-swipe (same)	Rear-end	Total
Crash Frequencies	-71.12%	-57.85%	33.24%	-51.88%
PDO Crashes	-79.44%	-52.05%	26.16%	-59.03%
Total Injuries	-46.09%	-70.26%	-12.57%	-40.34%

Figure 24: Simple before and after study results

The results should be interpreted taking into account the assumption that there are no changes in *before* to *program* periods other than the SEP. As discussed, the assumption may be questionable because numerous factors may influence safety, such as changes in traffic volume, geometry, signage, striping, weather, surrounding land uses, and driving populations. In the next sections, this questionable assumption is examined using other analysis methods.

4.4 Before and After Study with a Comparison Group

The simple BA study assumes that no changes other than the SEP have been implemented from the before to the program periods. However, it is necessary to adjust the impacts from the simple before-and-after study since there are a number of factors that may affect the safety. In general, the factors can be divided into 2 categories: recognizable and unrecognizable factors (Hauer, 1997). While the recognizable factors are measurable and can be modeled directly, unrecognizable factors such as the unobserved changes in driving population, traffic, weather, etc. can not be modeled easily.

In this section, the impacts of SEP on safety are adjusted by a comparison group approach. The key assumption for the comparison group method is that the ratio of the expected number of target crashes in both periods is the same for both the enforcement and comparison zones. This suggests that unobserved changes in safety, such as driving population, weather, etc., affect comparison sites in the same way as enforcement zone.

4.4.1 Overview of the Before and After Study with a Comparison Group

The basic concept of the before and after study with a comparison group is illustrated in Figure 25, in which k_i and l_j represent the observed number of target crashes at the enforcement zone during the before and program periods respectively, while m_i and n_j represent the observed number of target crashes at the comparison zone during the before and program periods respectively.

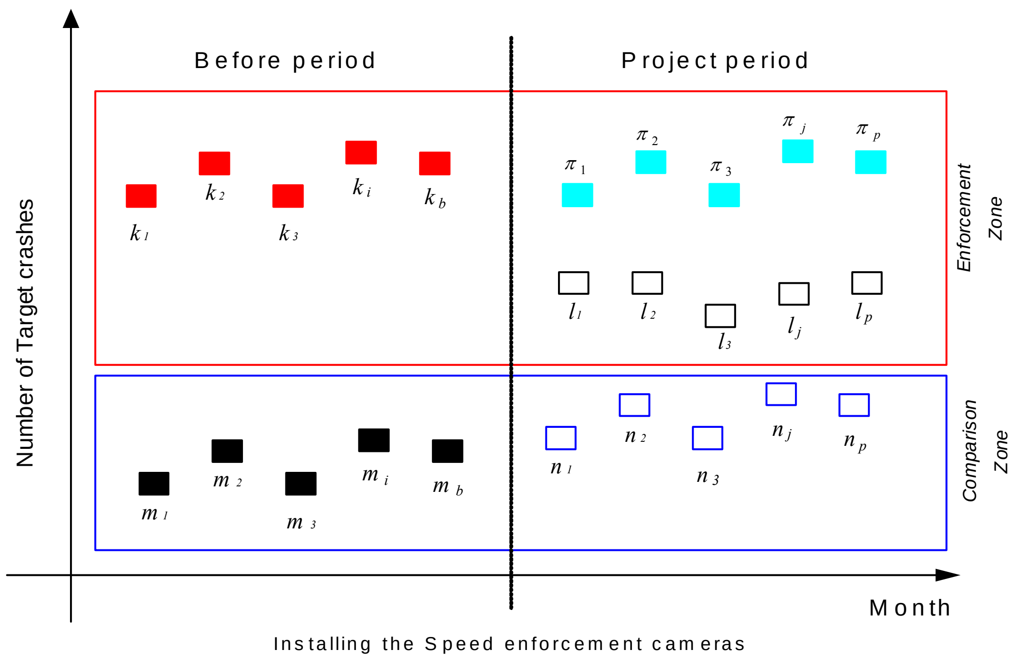


Figure 25: Basic concept of the before and after study with comparison group

Again, K, L, M, and N represent the sums of the observed number of crashes during each period. Table 28 shows the observed counts of crashes and the expected crash counts (Greek letters). These quantities are used to obtain the estimates in the before-and-after study with a comparison group.

Table 28: Key notations used in the before and after study with a comparison group

	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 during the program period. Unlike the simple before-and-after study approach, the comparison ratio can be used in order to estimate π:

$$\left(r_T = \frac{\pi}{\kappa}\right) = \left(r_C = \frac{\nu}{\mu}\right), \tag{8}$$

where these two ratios (r_T and r_C) are identical under the comparison group method assumption. Since the ratio r_C is a random variable consisting of a non-linear combination of two random variables (μ and ν) and the observed counts of target crashes at comparison sites are Poisson distributed, the estimate of π can be represented as Equation (9):

$$\hat{\pi}_C = \hat{r}_T \cdot K = \hat{r}_C \cdot K = \frac{\left(\frac{N}{M}\right)}{\left(1 + \frac{1}{M}\right)} \cdot K. \tag{9}$$

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 *L*, and the estimate of variance for $\hat{\pi}$ can be obtained by using the delta approximation:

$$\begin{aligned} \hat{\sigma}^2[\hat{\pi}] &= {r_T}^2 \cdot \hat{\sigma}^2[K] + K^2 \cdot \hat{\sigma}^2[\hat{r}_T] \\ &= \hat{\pi}^2 \cdot \left[\frac{1}{K} + \frac{\hat{\sigma}^2[\hat{r}_T]}{{\hat{r}_T}^2}\right]. \end{aligned} \tag{10}$$

For convenience, the ratio of r_T and r_C is defined as the odds ratio.

$$\omega = r_C / r_T \tag{11}$$

Therefore, the variance for $\hat{r}_T$ is:

$$\hat{\sigma}^2[\hat{r}_T] \cong \widehat{r_C}^2 \cdot \left(\frac{1}{M} + \frac{1}{N} + \frac{VAR[\omega]}{E^2[\omega]}\right). \tag{12}$$

By plugging Equation (12) into Equation (10), the estimate of variance for $\hat{\pi}$ can be rewritten:

$$\hat{\sigma}^2[\hat{\pi}] = \hat{\pi}^2 \cdot \left\{\frac{1}{K} + \left(\frac{1}{M} + \frac{1}{N} + \frac{VAR[\omega]}{E^2[\omega]}\right)\right\}. \tag{13}$$

With these corrections to the 4 step process, the remaining steps (step 3 and step 4) continue as before.

Table 29 shows the corrected 4-step used in the comparison method.

Table 29: Corrected 4-step for the before-after study with comparison group

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

4.4.2 Estimating Comparison Ratio

Figure 26 shows the comparison zone used in this analysis, which is 6.5 miles section on SR 101 west side. There are 2 assumptions in employing the comparison zone. First, the past crash trends within the comparison zone are similar to those within the enforcement zone. Second, the comparison zone is not affected by the SEP (i.e., not influenced by spillover effect).

(1) Enforcement zone: MP 34.51– MP 41.06 (Approximately 6.5 miles)
(2) Comparison zone: MP 3.5 – MP 10 (6.5 miles)

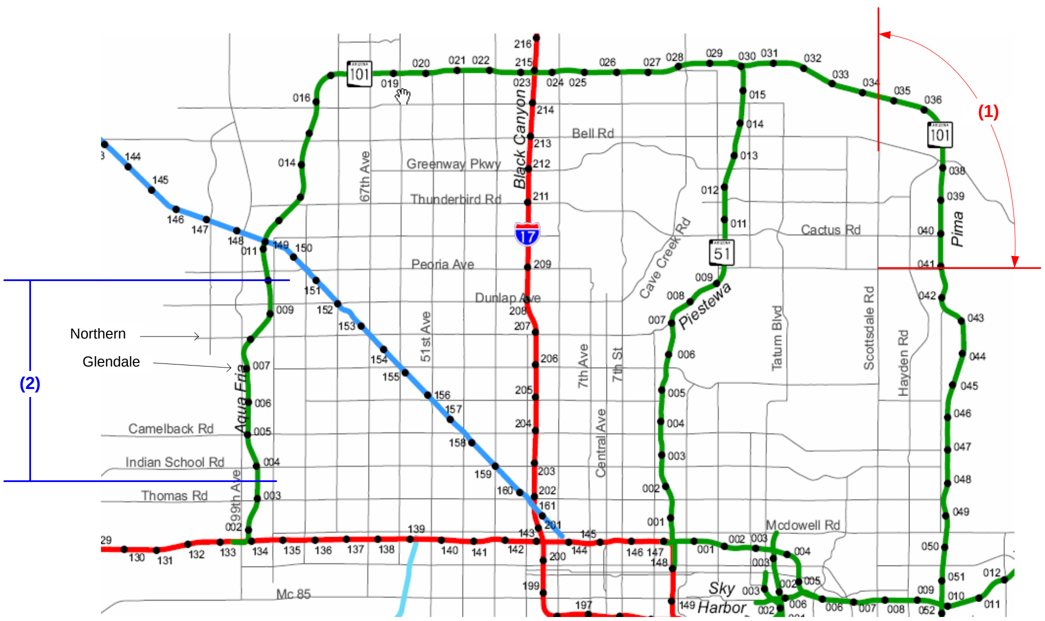


Figure 26: Enforcement and comparison zones

The first assumption can be statistically tested by the odds ratio (Hauer, 1997;Wong *et al.*, 2005). If the past crash trends within the comparison site are similar to those at the enforcement site, the odds ratio defined in Equation (11) should be equal to 1. Since the estimate of the odds ratio is also non-linear, an unbiased estimator is obtained using the delta approximation:

$$\widehat{\omega}_i = \frac{m_{i+1} \cdot k_i}{k_{i+1} \cdot m_i} \cdot \left(1 + \frac{1}{k_{i+1}} + \frac{1}{m_i}\right)^{-1}, \tag{14}$$

where $\widehat{\omega}_i$ is the estimate for the odds ratio during period *i* and the rest of the notation is as defined previously. Therefore, the average of the estimates for the odds ratios is

$$\overline{\widehat{\omega}} = \frac{1}{b-1} \cdot \sum_{i=1}^{b-1} \widehat{\omega}_i, \tag{15}$$

and the variance of the mean of the odds ratios is

$$S^2[\overline{\widehat{\omega}}] = \frac{1}{b-1} \cdot \left[\frac{1}{b-2} \left\{ \sum_{i=1}^{b-1} \hat{w}_i^{\,2} - (b-1)\overline{\widehat{\omega}}^{\,2} \right\} \right]. \tag{16}$$

If the confidence interval of the odds ratios does not include 1, the comparison zone should not be employed in the BA study with a comparison group. Table 30 shows the odds ratio test results for the comparison site illustrated in Figure 26. Since the estimates for the odds ratios are close to 1 and all 95% CIs contains the expected value 1 under the assumption of the BA study with a comparison group, the comparison zone is a suitable candidate. In addition, we assumed that the comparison zone was not affected by the SEP since there was no significant change (decrease) in speed from the before to the program period at the comparison zone (0.125 mph decrease; see 3.2.4 Changes in Mean Speed at the Comparison Site on page 47).

Table 30: Estimates for the odds ratios and 95% CI for the estimates

Collision type	$\overline{\widehat{\omega}}$	95% confidence interval	
		Lower	Upper
Single Vehicle	1.17	0.41	1.93
Side-swipe (same)	1.30	-0.65	3.25
Rear-end	1.01	-0.60	2.63
Other	1.89	-3.65	7.44
Total	1.21	0.19	2.23

Consequently, we estimated the comparison ratios from the comparison zone illustrated in Figure 26. The comparison ratio, (N/M)/(1+1/M), is the ratio of crashes before to program. Note that it is possible that the comparison ratios can be updated if there are other comparison zones whose variance of the odds ratios is relatively small. Table 31 shows the estimated comparison ratios and associated standard deviations. Comparison ratios greater than 1 indicate an increase, while ratios less than 1 indicate a decrease. For example, total crashes increased by 54% at the comparison zone.

Table 31: Estimates of the comparison ratio

Collision type	Comparison ratio (γ)	Std.Dev. (γ)
Single-vehicle	1.03	0.21
Side-swipe (same)	1.67	0.48
Rear-end	1.28	0.37
Other	3.80	0.67
Total	1.54	0.18

4.4.3 Results of the Before and After Study with a Comparison Group

Using the estimated comparison ratios shown in Table 31, the predicted values of π are obtained (see Equation (9)). Table 32 shows the estimated values for π, λ, δ, and θ as well as the estimated standard deviation for δ and θ.

Table 32: Results of before and after study with comparison group

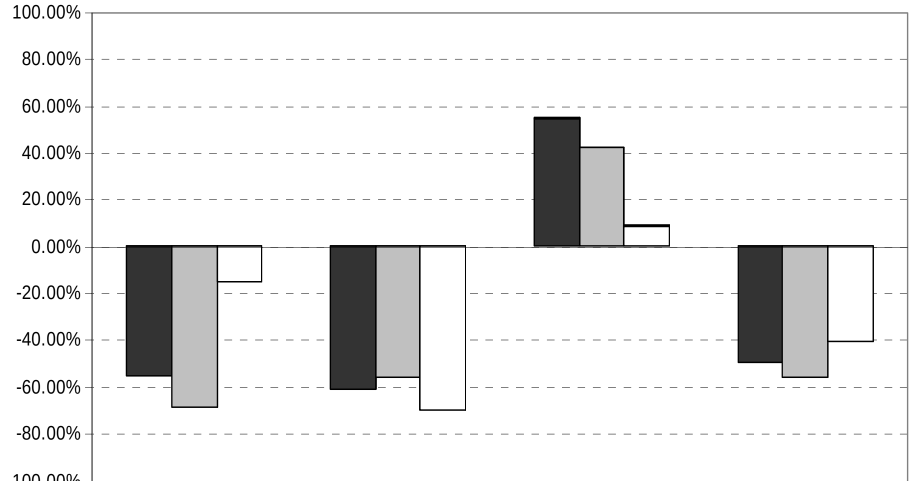
	Collision Type	Crash Estimates		Delta		Theta	
		Phi	Lambda	Estimate	Std.dev	Estimate	Std.dev
Total Crashes	Single Vehicle	30.53	14	**16.53**	6.67	**0.44**	0.21
	Side-swipe (same)	17.00	7	**10.00**	4.90	**0.39**	0.26
	Rear-end	11.30	19	-7.70	5.50	1.55	0.43
	Other	23.59	2	**21.59**	5.06	**0.08**	0.20
	Total	82.41	42	**40.41**	11.15	**0.50**	0.13
PDO Crashes	Single Vehicle	24.55	8	**16.55**	5.71	**0.31**	0.22
	Side-swipe (same)	12.67	6	**6.67**	4.32	**0.44**	0.30
	Rear-end	7.45	12	-4.55	4.41	1.42	0.49
	Other	15.98	1	**14.98**	4.12	**0.06**	0.24
	Total	60.64	27	**33.64**	9.36	**0.44**	0.15
Total Injuries	Single Vehicle	7.22	7	**0.22**	3.77	**0.85**	0.43
	Side-swipe (same)	5.67	2	**3.67**	2.77	**0.30**	0.38
	Rear-end	8.22	10	-1.78	4.27	1.09	0.44
	Other	11.41	1	**10.41**	3.52	**0.08**	0.27
	Total	32.52	20	**12.52**	7.25	**0.60**	0.21

* Bold numbers indicate crash reduction.

Since the comparison ratio for the rear-end crashes is greater than 1, the predicted values ($\hat{\pi}$) for the rear-end crashes are slightly greater than those from the simple before and after study.

Figure 27 illustrates the percent changes in target crash for each collision type and category. Again, the percent changes are $(\hat{\theta} - 1) \times 100$. Under the assumptions for the BA study with a comparison group, the results suggest:

- Total target crash frequency was reduced by 50%. Total PDO crashes and total injuries were also reduced by 56% and 40% respectively.
- Total crashes, PDO crashes, and total injuries of single-vehicle and side-swipe (same) crashes were reduced (15% to 70%).
- Total crashes, PDO crashes, and total injuries of rear-end crashes increased (9% to 55%).
    - Although rear-end crashes increased, the magnitudes of the increases are reduced when compared to those from the simple BA study.



	Single Vehicle	Side-swipe (same)	Rear-end	Total
Crash Frequencies	-55.60%	-61.11%	54.51%	-49.65%
PDO Crashes	-68.69%	-56.10%	42.08%	-56.20%
Total Injuries	-14.84%	-70.00%	8.50%	-40.33%

Figure 27: Results of before and after study with a comparison group

It should be noted that more comparison sites are needed to improve trend estimates, although the current comparison zone satisfies all of the assumptions required for a suitable comparison group.

4.5 Empirical Bayesian Before and After Study

In the previous approach the observed crash count in the before period (K) plays a key role in estimating π with the correction factor. However, it is also necessary to consider the possible regression-to-the-mean (RTM) bias in safety studies. In this section, the empirical Bayesian before and after study approach is applied to the crash data in order to correct the RTM bias.

4.5.1 Overview of Empirical Bayesian Method

In an observational study there is likely to be a link between the decision to treat an entity and its crash history. This link causes so called Regression-to-mean bias (RTM bias). If an entity is treated because its "before" accident count (K) was abnormally high or unusually low, then the same K can not be a good estimate of π (Hauer, 1997; Hauer *et al.*, 2002). In such circumstances, the best estimate of π is conditionally defined as E[κ|K], in which the observed crash K and the expected value κ are thought of as a *sample* and as a *prior* respectively in the Bayesian model. Then, the Bayesian theorem is expressed:

$$f(\kappa \mid K) = \frac{f(K \mid \kappa) \cdot f(\kappa)}{f(K)}, \tag{17}$$

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. Then, the posterior density of κ given K is calculated using the Bayesian theorem.

For a random sample of one segment, 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:

$$a = \frac{E[\kappa]}{V[\kappa]}, \quad b = \frac{E^2[\kappa]}{V[\kappa]} \tag{18}$$

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

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

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

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

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:

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

By plugging parameters a and b expressed by E[κ] and V[κ] in the prior distribution of κ (Equation (18)), they can be rewritten:

$$\begin{aligned} E[\kappa \mid K] &= w \cdot E[\kappa] + (1-w) \cdot K \\ V[\kappa \mid K] &= (1-w) \cdot E[\kappa \mid K], \end{aligned} \tag{19}$$

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

$$w = \frac{E[\kappa]}{E[\kappa] + V[\kappa]} \tag{20}$$

In Equation (19), E[κ|K] is interpreted as the expected count of crashes for a segment given observed crash frequency K, and E[κ] is the average crash frequency of the reference group, which is similar to the comparison group, but the reference group should have data about crashes as well as other covariates for the safety performance functions used in the EB method (will be discussed in the next subsection). In addition, V[κ|K] is the variance of crashes for a segment given observed crash frequency K. They are determined after obtaining the weight term shown in the Equation (20). The weight (w) consists of the average crash frequency of the reference group (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 segment of interest is close to the mean of its reference group (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).

The two components E[κ] and V[κ] play a pivotal role in obtaining the Bayesian estimator E[κ|K] as shown in Equation (20). In fact, the two components can be expressed by using the two parameters for the *prior*, which can be empirically estimated by the actual data (Carlin and Louis, 2000). In the Empirical Bayesian approach, it is common to assume that the crash frequency serves as data from a negative binomial distribution (Hauer, 1997;Hauer *et al.*, 2002). By using a negative binomial regression model, the two pivotal components can be estimated:

$$\widehat{E}[\kappa] = f(\text{covariates});\ \widehat{Var}[\kappa] = \widehat{E}^2[\kappa]\cdot\alpha;\quad \widehat{w} = \frac{\widehat{E}[\kappa]}{\widehat{E}[\kappa] + \widehat{Var}[\kappa]}, \tag{21}$$

where the estimate of E[κ] and an over-dispersion parameter α can be obtained by using the safety performance functions for the EB correction, which are discussed in the next subsection. Again, the 4-step to estimate the impacts of the SEP on safety can be corrected by using the results of the empirical Bayesian estimates.

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 during the program period, and the EB estimate of π is given by:

$$\hat{\pi} = \widehat{E}[\kappa \mid K] = \widehat{w}\cdot\widehat{E}[\kappa] + (1-\widehat{w})\cdot K. \tag{22}$$

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

The estimate of variance for $\hat{\lambda}$ is $\widehat{V}[\hat{\lambda}] = L$ 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,

$$\widehat{Var}[\hat{\pi}] = (1-\widehat{w})\cdot\hat{\pi}_{EB}. \tag{23}$$

The remaining steps (steps 3 and 4) proceed as previous. Table 33 shows the corrected 4-step used in EB method.

Table 33: 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	$\hat{\lambda} = L$ $\hat{\pi} = \widehat{E}[\kappa \mid K] = \widehat{w} \cdot \widehat{E}[\kappa] + (1 - \widehat{w}) \cdot K$
Step 2	Estimate $\hat{\sigma}^2[\hat{\lambda}]$ and $\hat{\sigma}^2[\hat{\pi}]$	$\widehat{VAR}[\hat{\lambda}] = L$ $\widehat{VAR}[\hat{\pi}] = \widehat{V[\kappa \mid K]} = (1 - \widehat{w}) \cdot \widehat{E[\kappa \mid K]}$
Step 3	Estimate δ and θ	$\hat{\delta} = \hat{\pi} - \hat{\lambda}$ $\hat{\theta} \cong \dfrac{\left(\dfrac{\hat{\lambda}}{\hat{\pi}}\right)}{\left(1 + \dfrac{\widehat{VAR}[\hat{\pi}]}{\hat{\pi}^2}\right)}$
Step 4	Estimate $\hat{\sigma}^2[\hat{\delta}]$ and $\hat{\sigma}^2[\hat{\theta}]$	$\hat{\sigma}^2[\hat{\delta}] = \hat{\pi} + \hat{\lambda}$ $\hat{\sigma}^2[\hat{\theta}] \cong \dfrac{\hat{\theta}^2 \cdot \left[\dfrac{\widehat{VAR}(\hat{\lambda})}{\hat{\lambda}^2} + \dfrac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^2}\right]}{\left[1 + \dfrac{\widehat{VAR}(\hat{\pi})}{\hat{\pi}^2}\right]^2}$

4.5.2 Developing Safety Performance Functions

In this section, we described the modeling approaches for developing the safety performance functions (SPFs), which need to be developed in order to obtain an estimate of the weight (*w*) in the empirical Bayesian before and after study. The SPFs were developed using negative binomial regression models, which are provided in the last subsection.

4.5.2.1 Data Description

In order to establish SPFs, a total of 52 sections on SR 101 were used. The number of sections may appear small but it covers more than 95% of the SR 101, which represents a total length of 60.19 miles. Traffic crash data during the same program period from 2001 to 2005 (a total of 3,495.6 total crashes) were used in the analysis in addition to the total PDO crash frequencies and total injuries. Therefore, the data used in the analysis have the pooled panel data structure.

Table 34: Summary Statistics for Variables in the Full Model (N=256)

Variable	Mean	Std. Dev.	Min	Q1	Q2	Q3	Max
Total crash frequency per section per 191 days	13.65	8.55	1.05	7.33	11.51	19.10	46.05
Total PDO crash frequency per section per 191 days	9.78	6.08	0	5.49	8.37	13.61	31.40
Total injuries per section per 191 days	5.90	4.69	0	2.35	4.71	8.37	27.21
AADT (vehicles/day)	113,561	33,999	52,000	83,200	115,000	142,000	196,000
Total length per section (miles)	1.15	0.41	0.50	0.99	1.03	1.22	2.53
Total Number of ramps per section	3.80	1.10	0	4.00	4.00	4.00	8.00
Average length of weaving area per section (miles)	0.31	0.25	0	0.19	0.25	0.35	1.40
Peak hourly volume (vehicles/hour)	6,482	1,127	4,284	6,127	6,342	6,468	10,278
Ratio of volume to service flow rate	0.98	0.18	0.63	0.87	0.95	1.07	1.56
Junction (1 or 0) : 1 if junction area	0.21	0.41	0	0	0	0	1.00
Lane reduction (1 or 0) : 1 for lane reduction	0.06	0.24	0	0	0	0	1.00

For each study section, a total of 8 possible explanatory variables were considered: average annual daily traffic (AADT), geometric features including total length, weaving section length, two variables related to congestion such as peak hourly volume and V/C ratio, and 2 dummy variables for junction-related and lane reduction. Table 34 shows the summary statistics for the variables listed above.

4.5.2.2 Count Models for Developing SPFs

The general approach used to develop SPFs involves the use of count based models. 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).

Poisson regression model is often used to fit models of the number of occurrences of an event. Let $y_i, i = 1, 2, \cdots, N$ be the observations of a discrete and non-negative integer variable, which is assumed to be independently Poisson distributed, with the conditional mean specified as:

$$E[\, y_i \mid \mathbf{x}_i \,] = \lambda_i = \exp(\mathbf{x}_i{}'\boldsymbol{\beta}) \tag{24}$$

where $\mathbf{x}_i$ is a $k \times 1$ vector of explanatory variables associated with the ith observation and $\boldsymbol{\beta}$ is a $k \times 1$ vector of unknown parameters. Equation (24) 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).

The density function of y_i given $\mathbf{x}_i$ is:

$$f(y_i \mid \mathbf{x}_i) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i\,!}. \qquad y_i = 0, 1, 2, \ldots \tag{25}$$

Therefore, the likelihood function can be obtained by multiplying the density function of y_i across all observations as follows:

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{n} \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i\,!} \tag{26}$$

and the log-likelihood function is

$$\begin{aligned} \ln L(\boldsymbol{\beta}) &= \sum_{i=1}^{n} [-\lambda_i + y_i \ln \lambda_i - \ln(y_i\,!)] \\ &= \sum_{i=1}^{n} \Big[-\exp(\mathbf{x}_i{}'\boldsymbol{\beta}) + y_i \mathbf{x}_i'\boldsymbol{\beta} - \ln(y_i\,!)\Big]. \end{aligned} \tag{27}$$

The unknown parameters $\boldsymbol{\beta}$ can be estimated by maximizing the log-likelihood function. The maximizing value for $\boldsymbol{\beta}$ denoted as $\hat{\boldsymbol{\beta}}_{ML}$, is derived by computing the first derivatives of the log-likelihood function:

$$\frac{\partial \ln L(\boldsymbol{\beta} \mid y)}{\partial \boldsymbol{\beta}} = \sum_{i=1}^{n} \left[-\mathbf{x}_i' \exp\left(x_i' \boldsymbol{\beta} \right) + y_i \mathbf{x}_i' \right] \tag{28}$$

and then solving the first order conditions for a maximum

$$\sum_{i=1}^{n} \left[-\mathbf{x}_i' \exp\left(\mathbf{x_i}' \boldsymbol{\beta} \right) + y_i \mathbf{x}_i' \right] = 0. \tag{29}$$

The standard errors of the unknown parameters are obtained from the inverse of the Hessian matrix of the log-likelihood function. The Hessian matrix is obtained from the second derivatives of the log-likelihood function with respect to $\boldsymbol{\beta}$.

$$H(\boldsymbol{\beta}; y, x) = \frac{\partial^2 \ln L(\boldsymbol{\beta} \mid y)}{\partial \boldsymbol{\beta}\, \partial \boldsymbol{\beta}'} = \sum_{i=1}^{n} \left[-\mathbf{x_i}' \, \mathbf{x_i} \exp\left(\mathbf{x_i}' \boldsymbol{\beta} \right) \right] \tag{30}$$

and then the variance of $\hat{\boldsymbol{\beta}}_{ML}$ is given by

$$\begin{aligned} Var(\hat{\boldsymbol{\beta}}_{ML}) &= \left(-E\left(\frac{\partial^2 \ln L(\boldsymbol{\beta} \mid y)}{\partial \boldsymbol{\beta}\, \partial \boldsymbol{\beta}'} \right) \right)^{-1} \\ &= \left(\sum_{i=1}^{n} -\mathbf{x_i}' \, \mathbf{x_i} \exp\left(\mathbf{x_i}' \boldsymbol{\beta} \right) \right)^{-1} \end{aligned} \tag{31}$$

It is necessary to note that the conditional mean $\lambda_i = \mu_i t_i$, in which μ_i is the incidence rate (probability of a new event per tiny time interval) and *t* is often referred to as the exposure. Therefore, Equation (24) can be rewritten:

$$E\left[y_i \mid \mathbf{x}_i \right] = \lambda_i t_i = t_i \exp(\mathbf{x}_i{}' \boldsymbol{\beta}), \tag{32}$$

where the coefficient of t_i is 1. However, the coefficient of t_i can also be estimated by inserting it into the exponential mean function: $E\left[y_i \mid \mathbf{x}_i \right] = \exp(\gamma t_i + \beta_1 + \cdots + \beta_k x_{ik})$. Notice that if t_i is the same for every observation, this term can be absorbed into the intercept.

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 ($E[y_i] < VAR[y_i]$). The most common is the negative binomial model, which arises from a natural formulation of unobserved heterogeneity (Greene, 2003). By introducing the unobserved heterogeneity into the conditional mean, Equation (24) can be rewritten:

$$E[\,y_i \mid \mathbf{x}_i, v_i\,] = \lambda_i^{*} = \lambda_i v_i = \exp(\mathbf{x}_i{}'\boldsymbol{\beta} + u_i), \tag{33}$$

where v_i is $\exp(u_i)$ and u_i reflects either specification error or the kind of the unobserved heterogeneity (Greene, 2003). Therefore, the conditional density of y_i is:

$$f(y_i \,|\, \mathbf{x}_i\,, v_i) = \frac{e^{-\lambda_i^{*}} \lambda_i^{*y_i}}{y_i\,!} = \frac{e^{-\lambda_i v_i}\,(\lambda_i v_i\,)^{y_i}}{\Gamma(y_i + 1)}. \tag{34}$$

Since it is impossible to condition on the unobserved v_i, the marginal density of $f(y_i \mid \mathbf{x}_i)$ is obtained by integrating the joint distribution over v_i:

$$f(y_i \,|\, \mathbf{x}_i) = \int_0^{\infty} f(y_i \,|\, \mathbf{x}_i\,, v_i) g(v_i) dv_i, \tag{35}$$

where v_i>0. Thus, a specific choice of $g(\bullet)$ defines the marginal density of $f(y_i \mid \mathbf{x}_i)$.

There have been three distributions for $g(\bullet)$: the gamma distribution, the inverse Gaussian distribution, and the log-normal distribution (Winkelmann, 2003). In this analysis, we chose the gamma mixture that is widely used in traffic safety studies. In the gamma mixture model, the density function of v_i is $\mathrm{Gamma}(a, b)$:

$$g(v_i) = \frac{v_i^{\,a-1} \cdot \exp(-v_i\,/\,b)}{b^a \cdot \Gamma(a)}, \quad \text{for} \quad v_i > 0 \tag{36}$$

where *a* is the shape parameter and *b* is the scale parameter of the gamma distribution. In order to reduce the number of parameters from two to one (for mathematical convenience), the model usually assumes that $v_i \sim \mathrm{Gamma}(1/\alpha, \alpha)$.

$$g(v_i) = \frac{v_i^{\frac{(1-\alpha)}{\alpha}} \cdot \exp(-v_i\,/\,\alpha)}{\alpha^{1/\alpha} \cdot \Gamma(1/\alpha)}, \quad \text{for} \quad v_i > 0 \tag{37}$$

As a result, the gamma distribution can be expressed by one parameter, and the mean and variance of the gamma distribution of the v_i are $E[v] = 1$ and $Var[v] = \alpha$.

By using Equations (35) and (37), the marginal density of $f(y_i \mid \mathbf{x}_i)$ can be obtained:

$$f(y_i \,|\, \mathbf{x}_i) = \frac{\Gamma(1/\,\alpha + y_i)}{\Gamma(y_i + 1)\Gamma(1/\,\alpha)} \left(\frac{1}{1 + \alpha\lambda_i}\right)^{1/\alpha} \left(\frac{\alpha\lambda_i}{1 + \alpha\lambda_i}\right)^{y_i}, \tag{38}$$

which is one form of the negative binomial distribution (Winkelmann, 2003) and it is defined as NB2. Therefore,

$$E[\,y_i \mid \mathbf{x}_i, v_i\,] = \lambda_i \tag{39}$$

and

$$Var[y_i \mid \mathbf{x}_i, v_i] = \lambda_i(1+\alpha\lambda_i) \tag{40}$$

Under this model, the ratio of the variance to the mean is $(1+\alpha\lambda_i)$, which can vary by individuals. The log-likelihood function is

$$\begin{aligned}\ln L(\boldsymbol{\theta} \mid y) = \sum_{i=1}^{n} \Big[& \ln\Gamma\left(\alpha^{-1}+y_i\right) - \ln\Gamma\left(\alpha^{-1}\right) - \ln\Gamma(y_i+1) \\ & + y_i \ln\alpha + y_i x_i'\beta - \left(\alpha^{-1}+y_i\right)\ln(1+\alpha\lambda_i)\Big].\end{aligned} \tag{41}$$

The unknown parameters, $\boldsymbol{\beta}$ and α (over-dispersion parameter), can be estimated by maximizing the log-likelihood function and derived by computing the first derivatives of the log-likelihood function with respect to $\boldsymbol{\beta}$ and α:

$$\frac{\partial \ln L(\boldsymbol{\beta} \mid y)}{\partial \boldsymbol{\beta}} = \sum_{i=1}^{n}\left[\frac{(y_i-\lambda_i)}{1+\alpha\lambda_i}\mathbf{x}_i'\right] \tag{42}$$

$$\begin{aligned}\frac{\partial \ln L(\boldsymbol{\beta} \mid y)}{\partial \alpha} = \sum_{i=1}^{n}\Big[& -\frac{1}{\alpha^2}\Psi\left(\frac{1}{\alpha}+y_i\right) + \frac{1}{\alpha^2}\Psi\left(\frac{1}{\alpha}\right) + \frac{y_i}{\alpha} \\ & + \frac{1}{\alpha^2}\ln(1+\alpha\lambda_i) - \left(\frac{1}{\alpha}+y_i\right)\frac{\lambda_i}{1+\alpha\lambda_i}\Big]\end{aligned} \tag{43}$$

where $\lambda_i = \exp(\mathbf{x}_i'\boldsymbol{\beta})$ and $\Psi(x)$ is a digamma function:

$$\Psi(x) = \frac{d\ln\Gamma(x)}{dx} = \frac{\Gamma'(x)}{\Gamma(x)}.$$

The standard errors of the parameters $\hat{\boldsymbol{\beta}}_{ML}$ and $\hat{\alpha}_{ML}$, are obtained from the inverse of the Hessian Matrix. The Hessian matrix is obtained from the second derivatives of the log-likelihood function with respect to $\boldsymbol{\beta}$ and α. The (2×2) Hessian matrix is given by:

$$H(\boldsymbol{\beta}, \alpha; y, \mathbf{x}) = \begin{bmatrix} \dfrac{\partial^2 \ln L(\boldsymbol{\beta} \mid y)}{\partial\boldsymbol{\beta}\,\partial\boldsymbol{\beta}'} & \dfrac{\partial^2 \ln L(\boldsymbol{\beta} \mid y)}{\partial\boldsymbol{\beta}\,\partial\alpha} \\ \dfrac{\partial^2 \ln L(\boldsymbol{\beta} \mid y)}{\partial\alpha\,\partial\boldsymbol{\beta}} & \dfrac{\partial^2 \ln L(\boldsymbol{\beta} \mid y)}{\partial\alpha\,\partial\alpha'} \end{bmatrix}. \tag{44}$$

In addition to Poisson regression model (PRM) and 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. Although fit may be improved, the theoretical support for a dual-state process is lacking. Inherently, "safe" locations do not agree with our understanding of crash causation. Thus, PRM and NBRM were employed to find SPFs comprising AADT and the number of crashes.

4.5.2.3 Modeling Results

Table 35 shows the developed SPFs estimated by using the NBRM. All estimated coefficients of independent variables and the log-likelihood ratio test for global test (H_0: the estimated model is not appropriate) are significant at α=0.05. In addition, the log-likelihood ratio tests for the over-dispersion is 0 in the negative binomial regression model, indicating that the negative binomial regression model is preferable to the Poisson regression model. Note that the SPFs for each crash type could not be developed due to the relatively small sample size.

Table 35: Developed SPFs for EB application

	Variable	Estimate	Std.Err.	P-value
Total Crashes	AADT (vehicles/day)	0.0000118	0.0000008	<0.0001
	Log of total length (miles)	1.058238	0.0960107	<0.0001
	Ave. length of weaving area (miles)	-0.3308705	0.1220948	0.007
	Junction	-0.1557225	0.066867	0.02
	Constant	1.209892	0.1029637	<0.0001
	Likelihood for the estimated model (χ^2 statistics and associated p-value)		-772.94 (χ^2=211.61; <0.0001)	
	Over-dispersion parameter α (standard error)		0.0892064 (0.0154967)	
	Likelihood ratio test statistics for H_0: α=0 (associated p-value)		χ^2=101.36 (<0.0001)	
	Variable	Estimate	Std.Err.	P-value
Total PDO Crashes	AADT (vehicles/day)	0.0000118	0.0000008	<0.0001
	Log of total length (miles)	1.059809	0.0969112	<0.0001
	Ave. length of weaving area (miles)	-0.3274636	0.1203517	0.007
	Junction	-0.1547298	0.0671788	0.021
	Constant	0.8791145	0.1044735	<0.0001
	Likelihood for the estimated model (χ^2 statistics and associated p-value)		-691.934 (χ^2=210.11; <0.0001)	
	Over-dispersion parameter α (standard error)		0.0599316 (0.0151396)	
	Likelihood ratio test statistics for H_0: α=0 (associated p-value)		χ^2=31.87 (<0.0001)	
	Variable	Estimate	Std.Err.	P-value
Total Injuries	AADT (vehicles/day)	0.0000122	0.0000011	<0.0001
	Log of total length (miles)	1.087034	0.1380414	<0.0001
	Ave. length of weaving area (miles)	-0.3890718	0.1716208	0.023
	Constant	0.2994693	0.1475718	0.042
	Likelihood for the estimated model (χ^2 statistics and associated p-value)		-636.236 (χ^2=128.39; <0.0001)	
	Over-dispersion parameter α (standard error)		0.1716398 (0.0312429)	
	Likelihood ratio test statistics for H_0: α=0 (associated p-value)		χ^2=86.73 (<0.0001)	

In all estimated models, the signs for AADT and length are positive, while the coefficients for average length of weaving area and the dummy variable junction are negative. Using these estimated SPFs, the EB weight (w) and the EB estimates (E[κ|K]) can be obtained as discussed in Equation (21), and Table 36 shows the estimated EB weight and the EB estimates. The enforcement zone was not the 'least safe' on SR 101 prior to the SEP program since the expected crash counts from the reference group are greater than the observed crash counts. Therefore, the EB estimate is greater than the observed crash count, but less than the expected crash count.

Table 36: EB weight and EB estimates

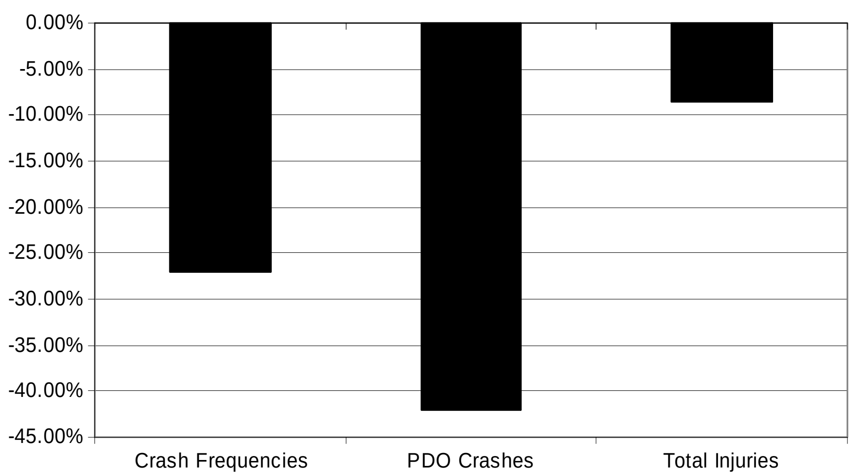
	Expected crash count (E[κ])	Observed crash count (K)	EB weight (*w*)	EB estimate (E[κ|K])
Total crashes	76.67	54.80	0.15	58.00
Total PDO crashes	55.07	41.40	0.30	45.54
Total Injuries	31.36	19.80	0.19	21.95

4.5.3 EB Before and After Study Results

Table 37 shows the EB before and after study results. After adjusting the RTM bias, the impacts of the SEP on safety slightly increased since the 101 Scottsdale enforcement zone was 'safer than average' prior to the SEP.

Table 37: EB before and after study results

	Crash Estimates		Delta		Theta	
	Phi	Lambda	Estimate	Std.Dev	Estimate	Std.Dev
Total crashes	58.00	42	15.00	10.05	0.73	0.17
Total PDO crashes	45.54	27	18.54	8.52	0.58	0.18
Total Injuries	21.95	20	0.95	6.55	0.92	0.28



	Crash Frequencies	PDO Crashes	Total Injuries
■ Off-peak	-27.12%	-41.99%	-8.49%

Figure 28: EB before and after study results

Figure 28 illustrates the percent changes in target crash for each analysis category. Again, the percent changes are $(\hat{\theta} - 1) \times 100$. The EB before and after study results suggest:

- The impacts of the SEP on safety are larger than those from the simple before and after study when accounting for the RTM bias. Specifically,
    - Total target crash frequency was reduced by 27%. Total PDO crashes and total injuries were also reduced by 41% and 8% respectively.
    - However, the reduction percentages are less than those from the before and after study with a comparison group.

4.6 Economic Analysis

In this section, the estimated changes in safety due to the SEP are translated into economic impacts. The conversion of crashes to crash costs is extremely beneficial and insightful because different crash types have different cost implications, with some crash types costing more than others. In order to quantify the economic impacts, the Arizona-specific crash costs were developed based on the crash costs obtained from several Arizona freeways, and the economic benefits from the SEP were estimated by using the crash costs and the estimated changes in safety (δ).

4.6.1 Arizona-specific Crash Costs

Crash costs are obtained from extensive national research on full costs of motor vehicle crashes (Blincoe *et al.*, 2002). In this analysis, the crash costs are updated to reflect Arizona -specific costs such as hospital charges by injury severity category and to reflect crashes on Arizona high-speed freeways. We utilized inflation adjusted costs from National Hospital Discharge Survey, National Health Interview Survey, AZ hospital cost/charge information, CHAMPUS data on physician costs, National Medical Expenditure Survey, National Council on Compensation Insurance, and Crashworthiness Data System.

Table 38: Estimated Arizona-specific crash costs

Collision type	Crash severity	Final Medical Cost	Total Other Cost	Quality of Life Cost	Total Cost
Single-vehicle	K	$162,870	$1,340,063	$2,111,828	$3,614,761
	A	$122,790	$200,291	$361,020	$684,101
	B	$24,104	$61,295	$88,104	$173,503
	C	$13,545	$34,771	$45,343	$93,659
	O	$15,527	$41,402	$50,277	$107,206
Side-swipe (same direction)	K	$119,065	$1,651,039	$2,496,842	$4,266,946
	A	$133,636	$301,959	$442,205	$877,801
	B	$27,504	$80,482	$86,291	$194,277
	C	$16,354	$65,398	$64,673	$146,425
	O	$15,826	$62,247	$50,530	$128,604
Rear-end	K	$71,037	$1,608,206	$2,441,687	$4,120,929
	A	$70,820	$162,469	$239,725	$473,013
	B	$39,899	$100,244	$152,827	$292,971
	C	$28,785	$77,037	$113,695	$219,517
	O	$30,643	$77,278	$117,022	$224,942
Other Crashes	K	$77,949	$1,200,900	$1,784,243	$3,063,092
	A	$97,374	$236,524	$310,713	$644,611
	B	$15,431	$62,216	$60,957	$138,604
	C	$8,557	$42,965	$43,917	$95,439
	O	$3,421	$34,919	$11,019	$49,359

All crash costs for each crash type are estimated by using a large sample of crashes that occurred on Arizona high-speed freeways (SR 101, 202, and 51). Table 38 shows the estimated Arizona-specific crash costs for each target crashes by severity level, in which the crash severity is classified by using the KABCO severity scale (K = killed; A = disabling injury; B = evident injury; C = possible injury; O = property damage only). The crash costs have 3 cost items:

- Medical Costs: Professional, hospital, emergency department, drugs, rehabilitation, long-term care
- Other Costs: Police/ambulance/fire, insurance administration, loss of wages, loss of household work, legal/court costs, property damage
- Quality of Life Costs: Based on Quality Adjusted Life Years (approximately $92k/QALY)

4.6.2 Economic Benefits

The economic benefits from SEP are quantified using the unit costs and the changes in safety (δ). The estimated changes in safety derived from the simple before and after study and before and after study with a comparison group are shown in Table 39. Note that the economic benefits from the EB before and after study are not quantified in this preliminary report because the estimates could not be obtained in terms of crash type and crash severity due to the small sample size.

Table 39: Changes in safety by severity

Analysis method	Collision type	Crash severity				
		K	A	B	C	O
Simple before and after study with traffic correction	Single Vehicle	0.23	-0.18	5.08	-1.58	29.91
	Side-swipe (same)	0.00	0.00	1.74	1.36	5.51
	Rear-end	0.00	-1.59	-0.14	-0.52	-3.49
	Other	0.41	0.23	0.50	0.84	5.96
Before and after study with a comparison group	Single Vehicle	0.21	-0.97	3.09	-2.35	16.55
	Side-swipe (same)	0.00	0.00	2.00	1.33	6.67
	Rear-end	0.00	-1.74	-0.46	-0.95	-4.55
	Other	0.76	0.76	1.52	3.57	14.98

By multiplying the unit costs by the changes in safety, the economic benefits ($) are obtained. Table 40 shows the economic benefits per the program period (i.e., 191 days). The total benefit from the simple BA study is $6.0 M per 191 days, while the BA study with comparison group yields an estimated benefit of $5.5 M per 191 days, which is larger than that from the simple before and after study. On a annualized basis the benefits are estimated to be $11.5 M and $10.6 M respectively for the two methods.

Table 40: Summary of economic benefits per the program period ($1,000)

Analysis method	Collision type	Crash severity K	A	B	C	O	Total
Simple before and after study with traffic flow correction	Single Vehicle	$831	-$122	$882	-$148	$3,207	$4,651
	Side-swipe (same)	$0	$0	$337	$199	$709	$1,245
	Rear-end	$0	-$753	-$42	-$114	-$785	-$1,693
	Other	$1,250	$148	$69	$80	$294	$1,841
	Total	$2,081	-$727	$1,246	$18	$3,425	$6,044
Before and after study with a comparison group	Single Vehicle	$746	-$663	$537	-$220	$1,774	$2,174
	Side-swipe (same)	$0	$0	$389	$195	$857	$1,441
	Rear-end	$0	-$825	-$135	-$208	-$1,024	-$2,191
	Other	$2,331	$490	$211	$340	$739	$4,112
	Total	$3,076	-$997	$1,002	$108	$2,346	$5,535

Table 41: Summary of economic benefits per year ($1,000)

Analysis method	Collision type	Crash severity K	A	B	C	O	Total
Simple before and after study with traffic flow correction	Single Vehicle	$1,589	-$233	$1,686	-$282	$6,128	$8,888
	Side-swipe (same)	$0	$0	$645	$380	$1,355	$2,380
	Rear-end	$0	-$1,439	-$80	-$217	-$1,499	-$3,235
	Other	$2,388	$283	$131	$154	$562	$3,519
	Total	$3,977	-$1,388	$2,382	$34	$6,546	$11,551
Before and after study with a comparison group	Single Vehicle	$1,425	-$1,266	$1,026	-$421	$3,390	$4,154
	Side-swipe (same)	$0	$0	$743	$373	$1,638	$2,754
	Rear-end	$0	-$1,576	-$257	-$397	-$1,958	-$4,187
	Other	$4,454	$937	$403	$650	$1,413	$7,857
	Total	$5,879	-$1,905	$1,914	$206	$4,484	$10,578

Under the assumption that the changes in safety during the 191 days are the same as those during a year, the economic benefits are annualized as shown in Table 41. The annualized economic benefits range from $11,551,000/year to $10,578,000/year, and the positive values indicate that the increase in rear-end crashes does not nullify the impacts of SEP on safety. Detailed costs assessments of economic benefits quantified by each crash cost item are summarized in Tables 42 and 43.

Table 42: Economic benefit from the simple BA with traffic correction per 191 days

Collision type	Severity	Medical cost	Total other cost	Quality of life cost	Total
Single Vehicle	K	$37,460	$308,214	$485,720	$831,395
	A	-$21,857	-$35,652	-$64,262	-$121,770
	B	$122,546	$311,623	$447,920	$882,089
	C	-$21,348	-$54,798	-$71,461	-$147,607
	O	$464,443	$1,238,418	$1,503,894	$3,206,755
Side-swipe (same)	K	$0	$0	$0	$0
	A	$0	$0	$0	$0
	B	$47,747	$139,717	$149,801	$337,265
	C	$22,209	$88,810	$87,826	$198,845
	O	$87,265	$343,233	$278,624	$709,122
Rear-end	K	$0	$0	$0	$0
	A	-$112,745	-$258,650	-$381,642	-$753,037
	B	-$5,666	-$14,235	-$21,701	-$41,602
	C	-$14,911	-$39,905	-$58,894	-$113,710
	O	-$106,881	-$269,544	-$408,173	-$784,599
Other	K	$31,803	$489,967	$727,971	$1,249,741
	A	$22,396	$54,400	$71,464	$148,260
	B	$7,654	$30,859	$30,234	$68,748
	C	$7,205	$36,176	$36,978	$80,360
	O	$20,382	$208,047	$65,650	$294,080
Total		$587,703	$2,576,682	$2,879,951	$6,044,336

Table 43: Economic benefit from the before and after study with a comparison group per 191 days

Collision type	Severity	Medical cost	Total other cost	Quality of life cost	Total
Single Vehicle	K	$33,597	$276,425	$435,624	$745,646
	A	-$118,936	-$194,004	-$349,688	-$662,627
	B	$74,582	$189,657	$272,608	$536,848
	C	-$31,829	-$81,703	-$106,547	-$220,079
	O	$256,926	$685,083	$831,943	$1,773,952
Side-swipe (same)	K	$0	$0	$0	$0
	A	$0	$0	$0	$0
	B	$55,008	$160,964	$172,581	$388,554
	C	$21,806	$87,197	$86,231	$195,233
	O	$105,507	$414,983	$336,869	$857,359
Rear-end	K	$0	$0	$0	$0
	A	-$123,456	-$283,222	-$417,898	-$824,577
	B	-$18,332	-$46,058	-$70,218	-$134,608
	C	-$27,229	-$72,873	-$107,549	-$207,651
	O	-$139,548	-$351,927	-$532,925	-$1,024,399
Other	K	$59,309	$913,728	$1,357,576	$2,330,613
	A	$74,089	$179,964	$236,412	$490,465
	B	$23,483	$94,677	$92,760	$210,920
	C	$30,509	$153,179	$156,574	$340,262
	O	$51,240	$523,026	$165,043	$739,309
Total		$326,725	$2,649,097	$2,559,397	$5,535,219

Chapter 5 Conclusions, Limitations, and Further Work

This report presents the preliminary analysis results of the speed enforcement camera demonstration program (SEP) that was implemented on Arizona state route 101 from January 2006 to October 2006. This study estimated the impacts of the SEP on traffic safety, speed, and speeding behavior. Note that the conclusions are based on incomplete data, and thus the conclusions are likely to be revised once the data are updated and additional analyses are completed.

Conclusions

This preliminary study—based on the analysis of a variety of limited datasets—suggests the following:

1. Detection frequencies (speeds > 76 mph) increased by about 836% after the SEP ended. The Scottsdale 101 SEP appears to be an effective deterrent to speeding in excess of 75 mph.
2. The SEP reduced average speeds in the enforcement zone by about 9.5 mph.
3. All crashes appear to have been reduced except for rear-end crashes. Increases in rear-end crashes are traded for reductions in other crash types. Also, severity of crashes decreased within all crash types.
4. Swapping of crash types are common for safety countermeasures—many countermeasures exhibit the ‘crash swapping’ phenomenon observed in this study (left-turn channelization, red-light cameras, conversion of stop signs to signals, etc.).
5. Total estimated SEP benefits range from \$11 M to \$10 M per year, depending on the analysis type and associated assumptions, which suggests that the increase in rear-end crashes does not nullify the effects of the SEP on safety.
6. Estimated benefits are conservative because the Scottsdale 101 site was safer than average prior to the SEP.
7. Results are conservative because additional costs and benefits have not been considered: incident related congestion, reduced manual enforcement costs, risk to officers, and travel time costs.
8. It is not clear which results are more reliable, the BA with correction for traffic, the comparison group BA, or the Empirical Bayesian analysis results. At this point all three results should be weighed and considered. All three methods predict benefits, and only one predicts injury increases by a very small amount. Additional analysis should shed light on which analysis outcome is likely to be more reliable.

Limitations

The results of this analysis should be treated with caution for a variety of important reasons:

1. The results are based on small and incomplete samples. The demonstration program, which was implemented on a 6.5 section over a period of 6 months, none-the-less results in a relatively small sample of crashes. Small numbers of crashes results in large variability and uncertainty surrounding the analysis results, especially fatal and severe crashes which have high associated crash costs. In addition, approximately 7 of the 9 months of the program are evaluated in this analysis. More complete analysis will yield more reliable results.
2. Random fluctuations in crashes are commonly observed, and can influence the results significantly. In particular, severe crashes including fatal crashes will significantly influence the benefit estimates associated with the analysis.
3. Taking into account traffic exposure increases over time will increase the estimate of the effectiveness—translating to increased benefits.
4. Trends in crashes on the 101 are based on a small sample obtained at the comparison site. Analysis of the entire 101 set of crashes will yield more reliable estimates of crash trends on the 101 from the *before* to *program* periods. Also, comparison crashes will be used to expand the analysis (i.e. crashes during peak periods).
5. Detailed analysis of specific crashes has not been conducted as part of this analysis, and may reveal trends in crashes that have not been revealed in this analysis, such as crashes caused by drivers under the influence of drugs or alcohol, crashes as a result of preceding incidents, or crashes as a result of construction projects.
6. The entire set of costs and benefits have not been included in this analysis. The costs of reduced travel times (lost productivity of drivers) have not been included. The additional benefits of reduced risk to law enforcement personnel, of reduced incident-related congestion, and reduced 'secondary' crashes have not been included.

Planned Further Work

Since the current analyses were conducted by using incomplete data, the analysis result will be updated during the spring of 2007, and presented in the Final Report. The planned further work includes:

- Analyze priority 3 crashes (i.e., all SR 101 crashes in 2006)
- Examine additional comparison sites and comparison crashes
- Examine car-following effects
- Update databases (detections and speed)

- Increase sample size of comparison sites to improve analysis consistency
- Focus on implementation recommendations and guidelines
- Compute additional costs and benefits of program, including travel time losses, incident related congestion costs, reduced enforcement costs, and reduced officer risk.

References

Blincoe, L., A. Seay, E. Zaloshnja, T.Miller, E. Romano, S.Luchter, and R.Spicer. (2002). "Economic Impact of Motor Vehicle Crashes, 2000." National Highway Traffic safety Administration.

Cameron, A. C., and P. K. Trivedi. (1998). *Regression Analysis of Count Data*, Cambridge University Press.

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

Champness, P., and L. Folkman. (2005). "Time and distance halo effects of an overtly deployed mobile speed camera." *The Australasian Road Safety Research, Policing and Education Conference Proceedings*, Accessed January 9, 2007 at http://www.rsconference.com/roadsafety/detail/2511.

Chen, G., W. Meckle, and J. Wilson. (2002). "Speed and safety effect of photo radar enforcement on a highway corridor in British Columbia." *Accident Analysis and Prevention*, 34(2), 129.

Cunningham, C. M., J. E. Hummer, and J. Moon. (2005). "An evaluation of the safety affects of speed enforcement cameras in Charlotte, North Carolina." Institute for Transportation Research and Education.

Elvik, R. (1997). "Effects on Accidents of Automatic Speed Enforcement in Norway." *Transportation Research Record 1595*, 14.

Goldenbeld, C., and I. van Schagen. (2005). "The effects of speed enforcement with mobile radar on speed and accidents. An evaluation study on rural roads in the Dutch province Friesland." *Accident; Analysis and Prevention*, 37(6), 1135.

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

Ha, T., J. Kang, and J. Park. (2003). "The effects of automated speed enforcement systems on traffic flow characteristics and accidents in Korea." *ITE Journal*, 73(2), 28.

Hauer, E. (1997). *Observational Before-After Studies in Road Safety: Estimating the Effect of Highway and Traffic Engineering Measures on Road Safety*, Pergamon, Elsevier Science Ltd., Oxford, U.K.

Hauer, E., F. J. Ahlin, and J. S. Bowser. (1982). "Speed enforcement and speed choice." *Accident Analysis & Prevention*, 14(4), 267.

Hauer, E., D. W. Harwood, F. M. Council, and M. S. Griffith. (2002). "Estimating safety by the empirical Bayes method: a tutorial." *Transportation Research Record 1784*, 126-131.

Hess, S. (2004). "Analysis of the Effects of Speed Limit Enforcement Cameras: Differentiation by Road Type and Catchment Area." *Transportation Research Record 1865*, 28.

Hess, S., and J. Polak. (2003). "Effects of Speed Limit Enforcement Cameras on Accident Rates." *Transportation Research Record 1830*, 25.

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

Lamm, R., and J. H. Kloeckner. (1984). "Increase of Traffic Safety by Surveillance of Speed Limits with Automatic Radar Devices on a Dangerous Section of a German Autobahn: A Long-Term Investigation." *Transportation Research Record 974*, 8.

National Highway Traffic Safety, A. (2005). "2004 Traffic safety fact sheets."

Pilkington, P., and S. Kinra. (2005). "Effectiveness of Speed Cameras in Preventing Road Traffic Collisions and related Casualties: Systematic Review." *British medical journal*, 330(7487), 331.

Retting, R. A., and C. M. Farmer. (2003). "Evaluation of Speed Camera Enforcement in the District of Columbia." *Transportation Research Record 1830*, 34.

Roberts, C. A., and J. brown-Esplain. (2005). "Technical Evaluation of Photo Speed Enforcement for Freeways." *ADOT-AZ-05-596*, AZTrans: The Arizona Laboratory for Applied Transportation Research.

Roess, R. P., E. S. Prassas, and W. R. McShane. (2004). *Traffic Engineering*, Pearson Prentice Hall, London.

Sisiopiku, V. P., and H. Patel. (1999). "Study of the impact of Police Enforcement on Motorists's Speeds." *Transportation Research Record 1693*, 31.

Transportation Research Board. (2000). *Highway Capacity Manual*, Washington D.C.

Vaa, T. (1997). "Increased police enforcement: effects on speed." *Accident; Analysis and Prevention*, 29(3), 373.

Waard, D., and T. Rooijers. (1994). "An experimental study to evaluate the effectiveness of different methods and intensities of law enforcement on driving speed on motorways." *Accident; Analysis and Prevention*, 26(6), 751.

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

Washington, S. P., and K. Shin. (2005). "The impact of red light cameras (Automated enforcement) on safety in Arizona." *FHWA-AZ-05-550*, University of Arizona.

Winkelmann, R. (2003). *Econometric Analysis of Count Data*, Springer, New York.

Wong, S. C., N. N. Sze, H. K. Lo, W. T. Hung, and B. P. Y. Loo. (2005). "Would relaxing speed limits aggravate safety? A case study of Hong Kong." *Accident Analysis and Prevention*, 37(2), 377-388.