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A Safety Evaluation of Photo-Red Enforcement Programs in Virginia

By

Rahul Khandelwal

Dr. Nicholas J. Garber

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Dr. Nicholas J. Garber
Department of Civil Engineering
Email: njg@virginia.edu

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CTS Website	Center for Transportation Studies
http://cts.virginia.edu	University of Virginia
	351 McCormick Road, P.O. Box 400742
	Charlottesville, VA 22904-4742
	434.924.6362

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16. Abstract

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An empirical Bayes approach was used to examine the impact of the program on crashes while controlling for mainline traffic volume, yellow interval, truck percentage, number of lanes, and speed limit. The use of the cameras were correlated with decreased red light running crashes (25% to 34%), increased rear-end crashes (45% to 65%), increased total crashes (5% to 13%), decreased injury crashes attributable to red light running (23% to 34%), and increased total injury crashes (4% to 20%).

Analysis of variance (ANOVA) and generalized linear models (GLMs) were used to control for confounding factors (such as average daily traffic, the yellow interval, and intersection geometry) and to pinpoint locations where use of photo-red enforcement can have a positive safety effect. ANOVA was used as an innovative screening tool to delineate the factors (including second order interaction terms) that potentially affect the crash frequency, and GLMs were used to quantify how these factors affect the crash frequency. The analysis illustrates the utility of selecting largest and most heterogeneous group of sites possible subject to the constraints 1) the geometric characteristics can be explicitly modeled and 2) the sites are homogenous in all other aspects not included in the model. Such sites can only be identified by detailed manual examination. The results suggest that photo red enforcement may have a positive impact on safety at intersections where the yellow interval is excessively higher than that recommended by ITE standards.

The crash results presented herein suggest that Virginia's program will realize a net safety gain if the severity of the eliminated red light running crashes is substantially greater than the severity of the induced rear end crashes. A detailed study of injury severity, therefore, is needed to determine if the cameras have a net safety benefit.

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A photo-red enforcement system entails the use of cameras that photograph vehicles entering an intersection after the signal has turned red; citations are then mailed to the vehicle's registered owner. The purpose of the research was to identify the safety impacts of photo-red enforcement programs in Virginia.

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1. INTRODUCTION

Red light running is a traffic safety problem that can result in injuries or fatalities. Motorists illegally enter the intersection on red, increasing the chance of a crash with a vehicle that enters the intersection legally. The results of a study conducted by the Insurance Institute for Highway Safety show that each year more than 800 people die and more than 200,000 people are injured in crashes involving red light running (IIHS, 2000). During the period 1992-1998, the total number of deaths in crashes involving red light running was approximately 6,000. More than half of these deaths were pedestrians and occupants in other vehicles hit by the illegal red light runners. During the same time period (1992-98), about 1,500,000 people were injured in illegal red light running crashes (IIHS, 2000). There were an estimated 7,800 Virginia drivers in 2001 who “disregarded stop-go light” which contributed to motor vehicle crashes. (The term “disregarded stop-go light” is one of the types of driver actions that may be indicated by the police officer on Virginia’s FR300 crash report form.) The figure does not include the 23,300 drivers charged with “failure to yield” nor the 31,700 drivers cited for “inattention.” (DMV, 2000).

In the United States photo-red enforcement systems have been in place for over 10 years. “Photo-red” is an automated enforcement system to detect and cite offending motorists. When a red light violation occurs, cameras capture all the relevant data of the violation such as the date, time, speed of the vehicle, and the time elapsed since the beginning of the red signal. Following a review and validation process, a citation showing photos of the violation is sent to the registered owner.

Virginia jurisdictions that have implemented a red light photo enforcement program include several Northern Virginia jurisdictions (Cities of Alexandria, Fairfax and Falls Church, the town of Vienna and counties of Fairfax and Arlington), as well as the City of Virginia Beach in the Hampton Roads area.

Each of the jurisdictions has adopted different criteria to select the intersections to be monitored. These criteria include frequency of red light violations, accident reports, intersection configuration, police and citizen input and difficulty of enforcement. For example, in Fairfax County, cameras are placed at locations where chronic red light violations create safety concerns. These locations are shown in Figure 1.1.

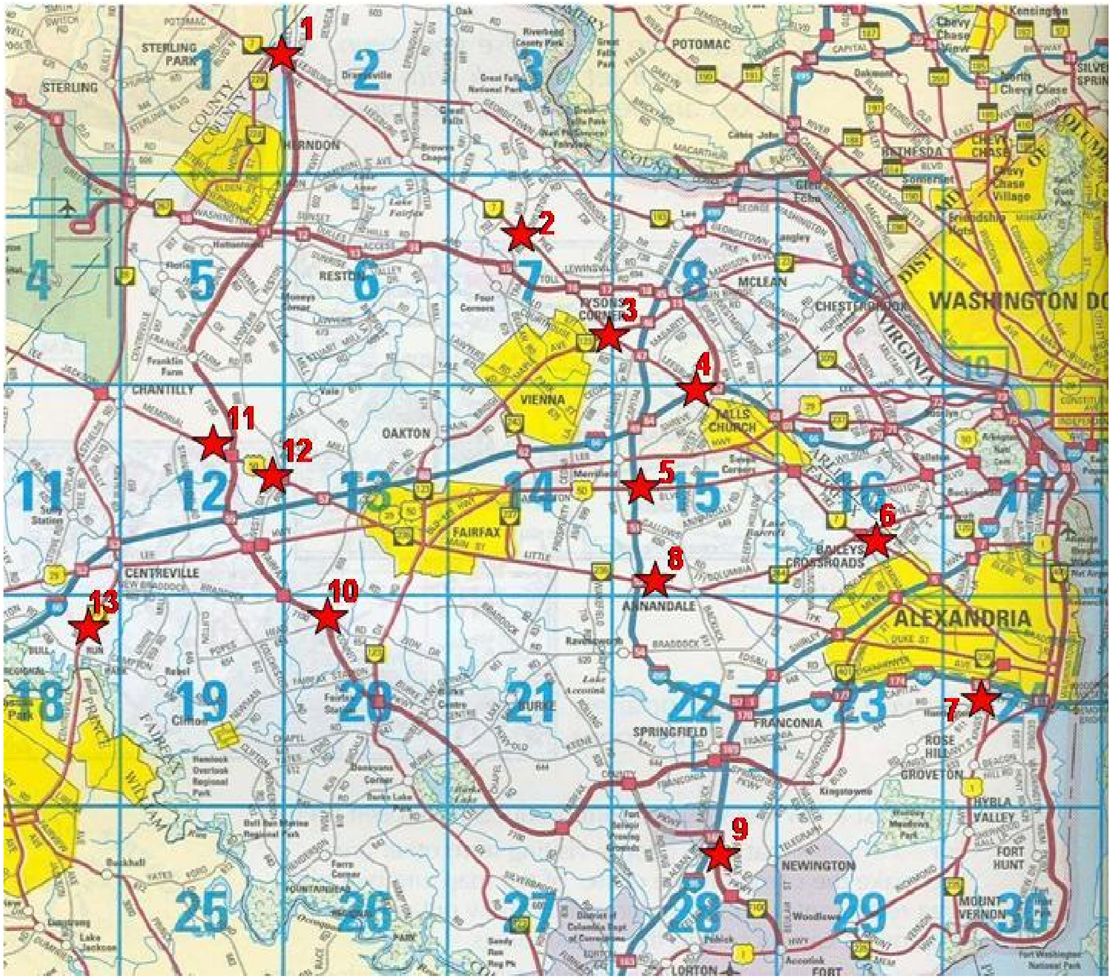

Figure 1.1 Camera Intersections (indicated by stars) in Fairfax County

1. Leesburg Pike, Dranesville Road (E.B.)
2. Leesburg Pike, Towlston Road (E.B.)
3. Leesburg Pike, Westpark Drive (W.B.)
4. Leesburg Pike, Route 66 (W.B.)
5. Arlington Boulevard, Jaguar Trail (W.B.)
6. Route 7, Carlin Springs Rd (W.B.)
7. Telegraph Road, Huntington Avenue (N.B.)
8. Route 236, Heritage Drive (E.B)
9. Fairfax County Parkway, Newington Road (N.B.)
10. Fairfax County Parkway, Popes Head Road (S.B.)
11. Lee Jackson Memorial Highway, Rugby Road (W.B.)
12. Lee Jackson Memorial Highway, Fair Ridge Drive (W.B.)
13. Route 28, Greens Trail Boulevard (S.B.)

Photo-red enforcement has received a great deal of attention from the media, the public and various government officials, and it has opponents as well as proponents. Advocates of red light camera programs assert that cameras improve safety at intersections by reducing the number of red light violations. Opponents, however, argue that the cameras are an invasion of personal privacy, that the purpose of red light cameras is to make money for the jurisdiction by ticketing drivers for non-serious (but technically valid) violations, and that red light running can be eliminated by simply increasing the yellow interval. For example, it is possible for the yellow interval to be too short, thereby creating what is known as the "dilemma zone". The "dilemma zone" is a region upstream of the intersection where motorists can neither safely stop nor cross the intersection before the red phase begins. In such a case the motorist may be ticketed unfairly. These opposing arguments make it necessary for a fair evaluation of the photo enforcement red light running program in Virginia.

Numerous studies have been carried out to evaluate the effectiveness of photo red light enforcement in reducing red light violations and crashes at intersections. Such studies usually suggest that red light camera enforcement reduces the number of red light violations and the ensuing number of angle crashes at the intersections (McGhee, 2003). This reduction is typically accompanied by a slight increase in rear end crashes. A net safety gain is realized at intersections by a higher reduction in angle crashes. In general, though, there is not enough convincing evidence to show that red light camera is an effective safety countermeasure and that safety is improved by deployment of such systems (McGhee, 2003). The aforementioned results have not been accepted because most of these studies had experimental or analysis flaws. For example, cameras are often placed at locations with high crash frequency resulting in regression to the mean effect. Regression to the mean effect is a selection bias that creeps in when camera intersections are selected based on intersection accident history. No account for regression to the mean effect has been given in the various studies, which could have caused an overestimation of the safety impact of photo enforcement. In some cases, results were statistically insignificant due to lack of sufficient data. Also, there is need for long-term study as the effect of any treatment changes over time due to road user adaptation with time has to be considered.

Thus, in order to determine the effectiveness of the red light cameras in Virginia, sufficient data must be gathered to detect statistically significant differences, should such differences be present. Sufficiently mature programs at some locations in Virginia provide an opportunity for effective evaluation with a sufficiently long duration of before and after records. A fair and comprehensive evaluation of the program will be helpful not only in settling the prevalent argument, but also in enabling the development of guidelines for various agencies on appropriate locations for deployment of cameras and in determining expected safety benefits of such systems.

1.1. Purpose and Scope

The purpose of this research is to identify the safety impacts of photo-red enforcement programs in Virginia measured in terms of violations and crashes. The scope of the study is limited to Virginia programs.

The objectives of the study are as follows:

1. To develop a comprehensive study methodology to determine the impact of photo red enforcement on safety.

2. To apply the methodology to determine the impact of photo red enforcement on overall safety.
3. To determine the effect of confounding factors such as yellow interval, speed and geometric characteristics of the intersection on crash frequency.
4. To provide recommendations to identify the intersections where photo red enforcement can be effective.

It was originally intended at the start of the study to analyze violation as well as crash data of all the jurisdictions in Virginia where active photo red enforcement was in place. However, because of the time constraints, it was later decided to analyze available detailed crash data for Fairfax County only. For other jurisdictions, sufficient data could not be collected in the study time frame. The selection of Fairfax County over other jurisdictions is warranted because:

- Fairfax County is the most populous county of Virginia with a population over one million people.
- The Fairfax County program had 13 intersections equipped with a photo enforcement system and was the biggest program in Virginia.
- The Fairfax County program was started in October 2000 and had three full years of operations by December 2003.
- For the other jurisdiction, sufficient data on confounding factors could not be collected in the given time frame.

The violation data were analyzed for the four jurisdictions for which data were available.

2. LITERATURE REVIEW

The literature review was conducted in which the published studies documenting the impact of photo-red enforcement on violations and crashes as well as the articles documenting "best practices" for applying photo-red programs were reviewed.

The articles came from diverse sources in terms of geography (e.g., the Australian Road Research Board, the United Kingdom's Central Research Unit, Canada's City of Edmonton, and the U.S. Transportation Research Board), type of organization (consulting firms, insurance organizations, and the federal government), and type of journal (e.g., *Journal of Public Health, Institute of Transportation Engineers (ITE) Journal*, *Urban Transportation Monitor,* and the *Triangle Business Journal*).

The results are summarized in Table A1 of Appendix A.

2.1. Published Studies

The results of more than two-dozen studies or evaluations have been published on the topic of red light cameras in the United States and abroad. The studies may be classified into three broad categories: the impact of the cameras on violations at the traffic signal, the impact of cameras on various types of crash rates, and recommended best practices for agencies that are considering the use of these cameras.

Violation Studies

Red light camera programs within and outside the United States have reported reductions in red light violations after the installation of cameras. As shown in Appendix A, a larger number of studies have examined changes in violation rates. Maccubbin et al. (2001) reported that reduction figures range from 20% to 87% for jurisdictions in United States, with half of the jurisdictions reporting between 40% and 62%. Figures were similar for programs in Australia, Singapore, Canada, and the United Kingdom (Winn, 1995; Mullen, 2001, Lum and Wong, 2003; Zaal, 1994; Chin, 1989). The Insurance Institute for Highway Safety reported a 40% reduction in red light violations in Oxnard, California (Retting et al., 1999b). Reductions in red light violations at the nearby signalized intersections without cameras were found to be identical with those at the photo-enforced intersections. This suggests that photo-enforcement not only reduces violations at the particular signal but also improves driver compliance at other signals in the same jurisdiction, also known as a “spillover” effect.

Two studies have evaluated the impact of cameras on red light violations in Virginia (Retting et al., 1999c, Ruby and Hobeika, 2003). Violation rates decreased by 36% over the initial 3 months and by 69% after 6 months (Ruby and Hobeika, 2003). The Insurance Institute for Highway Safety study showed reductions at the five camera sites were 7% after 3 months and 44% after 1 year. The study also noted that public support for camera use increased from 75% before enforcement to 84% 1 year after enforcement (Retting et al., 1999c).

Ideally red light violations at a particular intersection should be compared before and after the traffic signals are installed. However, prior to camera installation, there is often no complete set of violation data, because it is with the camera that automated data can be obtained (Retting et al., 1999c). However, some researchers collected “before” data with cameras or video recorders prior to camera installation (Lum and Wong, 2003). Generally, large reduction in violations after the installation of cameras has been reported.

The type of violations affected by the cameras also requires examination. Winn (1995) studied the impact of cameras on the number of violations at different time periods during the red signal phase. The study revealed that the decline in violations was greatest during the periods of 0.5 and 1.0 second into the red, i.e., 42% of total violations. In comparison, the number of violations occurring more than 5 seconds into the red was less than 1% of the total recorded violations. This type of analysis illustrates how red light cameras may change particular aspects of motorists' behavior. However, because studies such as Winn's have been conducted abroad (Scotland), more detailed data based on the U.S. experience are needed.

Crash Studies

Several studies have evaluated the impact of red light cameras on crashes, both in the United States and abroad, as shown in Appendix A. The majority of the studies reported a decrease in angle crashes with a slight increase in rear-end crashes (Hillier et al., 1993; Mann et al., 1994; Fox, 1996; Retting and Kyrychenko, 2002). To the extent angle crashes are more severe than rear-end crashes, a net safety gain is realized if the reduction in angle crashes is greater as compared to the increase in rear-end crashes. Although there is some evidence of a spillover effect, some studies indicate no such effect (Hillier et al., 1993).

Table A-2 of Appendix A provides the results of crash evaluations after installation of cameras as reported by various jurisdictions based on a survey conducted for the National Cooperative Highway Research Program (McGee and Eccles, 2003). The information includes location, type of evaluation, and findings for each jurisdiction that responded to the survey. Almost all the jurisdictions reported a reduction in crashes, although some noted an increase in rear-end crashes at camera intersections.

The red light camera programs are relatively older in Europe and Australia as compared to United States, which is the reason many of their evaluations are better able to examine the longer-term impacts of red light cameras. The results of these studies are mixed: a few studies (Hillier et al., 1993; Fox, 1996) show a reduction in crashes, and others (Andreassen, 1995) show an increase. A study with a 5-year before period and a 5-year after period performed in Australia that compared crashes at 41 enforcement sites found no long-term reduction in crashes and an increase in the rear-end crashes after the installation of the cameras (Andreassen, 1995). One study in Australia showed a 40% reduction in angle crashes with no increase in rear-end crashes (Office of Auditor General, 1993). Another Australian study showed a 50% reduction in angle and right-turn opposing crashes and 20% to 60% increase in rear-end crashes (Hillier et al., 1993). A Scottish study indicated significant benefits after installation of cameras based on a 3-year before and a 3-year after period (Fox, 1996). However, the author stated that the impacts of cameras could not be isolated, as engineering improvement in intersections during the study period might have also influenced the reduction (Fox, 1996). Another Australian study found that crashes at the sites with red light cameras and other modifications decreased significantly more than in the control group (Mann et al., 1994). Because of these other modifications, such as an increase in yellow interval from 3 to 4 seconds throughout the metropolitan area during the study period, the crash reductions cannot be said to be solely attributable to photo-red enforcement. Another methodological issue with the study was that cameras were installed at high-risk sites, and thus the sites were not comparable to the control sites.

A few U.S. studies focus on crash impacts. Three are from Oxnard, California (Retting and Kyrychenko, 2002) and Fairfax County, Virginia (Ruby and Hobeika, 2003; BMI, 2003). Citywide crash data for Oxnard were compared with the citywide crash data for three comparison cities. Crashes at signalized intersections throughout Oxnard were reduced by 7%. Injury crashes, total right angle crashes, and right angle crashes involving injuries throughout the city were reduced by 29%, 32%, and 68% respectively (Retting and Kyrychenko, 2002). Although cameras were installed at only 11 of 125 signalized intersections in Oxnard, crash reductions at signalized intersections were found on a citywide basis. The authors suggested that the cameras can change driver behavior and can provide general deterrence against red light violations, as the crash reductions are not limited to intersections with cameras (Retting and Kyrychenko, 2002).

A Fairfax County assessment showed a 40% reduction in accidents after 3 months of camera operation (Ruby and Hobeika, 2003). A limitation of the study, however, was that it covered only a 3-month period. Another recent study that compared crash frequencies and crash rates at camera intersections and 40 reference intersections in Fairfax and Prince William counties did not detect any effect from the cameras and recommended reanalysis of the data as the study was based on a very limited (less than 18 months for most of the camera intersections) after period and a small sample size (BMI, 2003).

A fourth study suggested that red light cameras have a negative impact. Burkey and Obeng (2004) found that based on a before-after comparison in Greensboro, North

Carolina, of 303 intersections over a 57-month period that red light cameras did not reduce crashes or severity; in fact, they increased crash rates by 40%. Further the authors found no other positive impacts—with one exception: a decrease in crashes that involved "a left turning car and a car traveling on a different roadway"—a type of crash that may be considered as an "angle" crash (Burkey and Obeng, 2004).

A most recent study found crash effects that were consistent in direction with those found in our study and in other previous studies i.e. increase in rear end crashes and decrease in angle crashes (Council et al., 2005). The study also conducted an economic effect analysis to assess the extent to which the increase in rear end crashes negates the benefits due to reduction in angle crashes based on an aggregation of rear end and right angle crash costs for various severity levels. The study showed that cameras provide modest to moderate economic benefit of between $39000 and $50000 per treated site year.

Best Practices

From a public policy perspective, the purpose of the red light camera is to increase safety at signalized intersections by reducing red light violations and the resultant crashes attributable to red light running. Guidance has been issued on the proper use of red light cameras.

The National Highway Traffic Safety Administration (NHTSA) and the Federal Highway Administration (FHWA) have published guidance for implementation and operation of the red light camera systems. The report (NHTSA and FHWA, 2003) provides a systematic approach to identify intersections with a red light running problem and the feasible countermeasures to address it. It suggests that appropriate cost-effective engineering, educational, and traditional enforcement solutions should be considered before deciding to use red light running cameras to enhance intersection safety. It lists the key steps to implement the red light camera program. These steps include establishing an oversight committee, establishing program objectives, and identifying legal requirements. The report provides guidance for camera system installation, operation and maintenance, citation data processing, and a public information campaign. These procedures however, are based on engineering judgment but are not driven by data.

The Institute of Transportation Engineers (ITE) has issued a report that identifies various engineering features at an intersection that should be considered to curb the problem of red light running (ITE, 2003). The report provides a background on the characteristics of the problem; identifies how various engineering measures can be implemented to address it; suggests a procedure for selecting the appropriate engineering measures; and provides guidance on when enforcement measures, including red-light cameras, may be appropriate.

In 2002, VDOT's Traffic Engineering Division has developed a seven-step process for selecting sites where photo-red enforcement is a suitable countermeasure (VDOT, 2002). The process includes determining the appropriate yellow interval, considering other countermeasures that may be implemented before or in lieu of photo-red enforcement, studying crash and violation data, reviewing physical characteristics of the intersection, and instituting a public awareness campaign.

2.2. Limitations to Findings in the Literature

The literature clearly suggests that red light cameras have contributed to reductions in violations. Firm proof remains elusive. Although several studies have suggested a reduction in crashes, at least one study suggests an increase. Further, there are limitations with the analyses, including the following:

- Most of the programs studied (BMI, 2003; Ruby and Hobeika, 2003; Retting et al., 1999c) were new with only 1 to 2 years of after camera data. Thus, long-term camera impacts were difficult to determine.
- In many studies, no reference sites were identified for comparison with the camera sites, introducing a potential bias in the evaluation. Generally, cameras are installed at the intersections with higher crash rates. Yet, there is random variation in the number of crashes from year to year at any particular intersection; it is possible that after a particularly "bad" year, the crashes will drop the following year for no reason except this random variation. This is called the regression to the mean phenomenon. Thus, if before and after crash frequencies are compared at an intersection, there is the possibility that a future drop in crashes will be erroneously attributed to the installation of a camera rather than being correctly attributed to random variation. To account for this potential bias introduced by the phenomenon, reference sites should be included in the analysis.

3. METHODOLGY

To determine the impacts of red light cameras on safety, a statistical analysis was conducted to quantify how such cameras affected and citations (validated red light violations). To ensure that confounding factors were controlled in this experiment, four tasks were undertaken.

1. Document Virginia's programs
2. Select appropriate comparison sites
3. Collect data
4. Analyze crash and citation data

3.1. Documentation of Virginia Programs

Representatives from seven jurisdictions that maintain a photo-red program in Virginia (City of Alexandria, Arlington County, Fairfax City, Fairfax County, City of Falls Church, the Town of Vienna, and the City of Virginia Beach) were contacted by phone, fax, and email regarding the status of their programs. Each jurisdiction received two customized surveys; an example of each is shown in Appendix B. The first survey sought basic program information pertaining to cost, placement of the cameras, intersections under study, and procedures for operating the cameras. The second survey, distributed a few weeks later, investigated the feasibility of obtaining more detailed crash and citation data from the jurisdictions. Additional phone calls and electronic mailings were necessary to clarify data details associated with operating the program, and phone calls to system vendors clarified how the technology functions.

Virginia's seven jurisdictions that operate photo-red programs have several similarities in terms of how they manage their programs. All seven of Virginia's programs indicated common objectives: to reduce violations, to reduce crashes, to increase pedestrian safety, and to change driver behavior. In terms of choosing where to place the cameras, most representatives of the jurisdictions surveyed indicated a combination of factors: crash and violation data, input from citizens and law enforcement, and a review of the site. Arlington County noted just three of those factors: crashes, input from citizens, and input from law enforcement. For most jurisdictions, the grace period (lag time) varied between 0.1 and 0.4 seconds and the reasons for the variation appear to be when the program was started, the technology in place, and information available to the jurisdiction. For example, Fairfax City indicated that the reason they have the largest lag time (0.4 second) is because they had the first program and wanted to be conservative in terms of issuing citations; the most recent jurisdiction to initiate a program (Virginia Beach) uses a time of 0.3 second based on a recommendation it obtained from a North Carolina study. The Town of Vienna does not have a set grace period per se. Table 3.1 summarizes key characteristics of each program.

Table 3.1 Overview of Virginia Photo-Red Programs

Jurisdiction	Program Start Date	Number of Cameras	Lag Time (sec)	Yellow interval (sec)[a]	Vendor	Camera Technology	Contractor Payment Method
Alexandria	11/97	3 rotated among 4 locations	0.3	3.0 to 5.0	ACS	35 mm wet film	Flat fee
Arlington	2/99	5 stationary	0.1	3.5 to 4.5	ACS	35 mm wet film	Flat fee
Fairfax City	7/97	7 stationary	0.4	3.5 to 4.5	ACS	35 mm wet film	Flat fee for equipment + a fee per citation
Fairfax County	10/00	13 that have been used in 15 locations	0.2	4.0 to 5.5	ACS	35 mm wet film	Flat fee for equipment + a fee per citation
Falls Church	10/00	8 stationary	0.1	3.0 to 4.0	Nestor Traffic System	Digital video	Flat fee
Virginia Beach	7/04	10 stationary	0.3	3.75 to 4.25	Redflex Traffic Systems	Digital video and digital still photos	Flat fee.
Vienna	6/99	3 stationary	Officer's discretion	4.0	Nestor Traffic System	Digital video	Flat fee for equipment + fee per citation that decreases as number of citations increases

[a]Yellow intervals provided in the table are based on current data; in some cases these have increased from the past.

3.2. Selection of Comparison Sites

The use of non camera comparison sites is essential for the before and after period comparison method called Empirical Bayes method used for Fairfax County crash data in this study. The Empirical Bayes (EB) method is described in Chapter 4. The EB method requires selection of comparison sites having characteristics, which can affect occurrence of red light running crashes, similar to the camera sites.

For this type of studies, two types of comparison sites could be of interest:

(1) Sites within jurisdictions where cameras are already in place (which have the advantage of having similar driver populations to the camera sites) and

(2) Sites in those jurisdictions where no cameras are in place (having the advantage of no spillover effects).

In this study 33 comparison sites within Fairfax County were identified and were used for analysis along with 13 camera sites in Fairfax County. These sites were selected based on recommendations from VDOT staff who had funded a previous study of Fairfax County's photo-red program (BMI, 2003). A list of all the camera and non camera sites selected is given in Appendix D. Since the main objective of the study was to evaluate the effectiveness of photo red enforcement on safety, one important criterion for site selection was availability of crash records for sufficiently long before and after periods.

For the other methods (Analysis of Variance and Generalized Linear Modeling) used in this study, it was not essential to use comparison sites. Yet the comparison sites data were used to increase the sample size.

3.3. Data Collection

Detailed data on citations, crashes and traffic engineering factors were collected, and carefully screened before the analysis could begin. All data elements shown herein were thought to be correct as of June 30, 2005. It should be noted, however, that many of these data elements, such as historical yellow interval at a particular signal or intersection grade, either were not documented formally by a single source or were given conflicting values from two different sources. For example, yellow intervals for Fairfax County sites were documented by examining excel spreadsheets and Synchro files provided by

Northern Virginia Traffic Engineering Division. The present yellow intervals were easy to document, however, it was difficult to get accurate historic yellow intervals with the dates when the yellow intervals were changed in the past. The documentation of historic yellow intervals entailed extracting data from a number of spreadsheets and Synchro files. Efforts such as, sending the documented spreadsheet back to the Northern Virginia Traffic Engineering Division for verification, were made to make sure that the data was correct before it was used for analysis. However, later, after the analysis was completed, it was found out that one of the values for yellow interval was incorrect. Thus despite efforts to ensure correct data were made; it is possible that data discrepancies will still be uncovered in the future.

Citation Data

Citation data were sought from the six jurisdictions that had an operational program as of July 2003 and from each of the two vendors that serve the jurisdictions: Affiliated Computer Services, Inc. (ACS), which covers Alexandria, Arlington, Fairfax City, and Fairfax County, and Nestor, Inc., which covers Falls Church and Vienna. Virginia Beach is served by RedFlex Traffic Systems, Inc., but their program did not begin until September 2004.

Ultimately, reliable citation data were successfully obtained from four jurisdictions: Alexandria, Arlington, Fairfax County, and Vienna. The citation data included time and date of the citation issued as well as *time in red*. The *time in red* here indicates the time duration for which the signal has been red when the vehicle crossed the stop line. Citation data reflect the number of citations mailed out (i.e., the number of actual violations), not the number of events where a vehicle was photographed.

Crash Data

Crash data were sought for January 1, 1998, through December 31, 2003, which, for most of the signals in Fairfax County, reflected a period before and after the cameras were installed. Camera installation dates varied for the different intersection in Fairfax County as shown in Table 3.2.

Table 3.2 Summary of Camera Locations in Fairfax County Where Data were Available

			Duration in Years		
Intersection	Camera Start Date	Camera End Date	Before Period	After Period	Removal Period
Route 236/Heritage Drive	9/9/2002	12/31/2003*	4.7	1.3	--
Route 28/Old Mill Road	6/15/2001	3/19/2003	3.5	1.8	0.8
Route 50/Fair Ridge Road	2/9/2001	9/9/2002	3.1	1.6	1.3
Route 50/Jaguar Trail	5/2/2001	12/31/2003*	3.3	2.7	--
Route 50/Rugby Road	2/9/2001	7/15/2004	3.1	2.9	--
Route 7/Carlin Springs Road	3/24/2003	12/31/2003*	5.2	0.8	--
Route 7/Dranesville Road	6/21/2001	12/31/2003*	3.5	2.5	--
Route 7/Interstate 66	5/2/2001	12/31/2003*	3.3	2.7	--
Route 7/Towlston Road	10/1/2000	3/14/2003	2.8	2.4	0.8
Route 7/Westpark Drive	3/22/2001	12/31/2003*	3.2	2.8	--
Route 7100/Newington Road	10/1/2001	12/31/2003*	3.8	2.3	--
Route 7100/Popes Head Road	7/10/2001	12/31/2003*	3.5	2.5	--
Telegraph Road/Huntington Road	3/18/2003	12/31/2003*	5.2	0.8	--
Total duration in intersection-years			48.2	26.9	2.9

*Cameras were still operating in the field after this date, but all data collection ended by December 31, 2003.

Crash data for the 13 camera sites came from two sources: a spreadsheet provided by Fairfax County and VDOT's Oracle databases, which became available in August 2004. Crash data for 33 comparison sites came from manual examination of crash report forms, i.e., the FR300 forms (FR300s) provided by VDOT's Traffic Engineering Division. These sites were selected based on recommendations from VDOT staff that had funded a previous study of Fairfax County's photo-red program (BMI, 2003).

Substantial effort was required to obtain the raw data, verify their accuracy, and synthesize them into a format suitable for analysis.

Crashes were classified by reviewing the FR300 form including the diagram and narrative. This method generally is viewed as quite precise, but it is also labor intensive. Five specific categories of crashes were studied: rear-end crashes, crashes attributable to red light running, injury crashes attributable to red light running, total injury crashes, and total crashes. A crash was classified as rear-end if the FR300 Collision type was coded as "rear end" *crash* or the narrative indicates that the front driver was stopped or stopping when struck from behind. A crash was categorized as red light running if the collision type was coded as "disregarded stop-go light" or if the narrative clearly states that one driver ran the red light. Injury crashes attributable to red light running were classified based on the standards for red light running crashes, except that the injury count must be greater than or equal to one. Total injury crashes included all crashes at an intersection where the injury count is greater than or equal to one. As was the case with other four categories, total crashes included all crashes within 150 feet of the intersection.

The detailed criteria based on which the classification of crashes was done is explained in detail in Table 3.3. The categories of crashes shown are not mutually exclusive. Thus, it is possible for a single crash to have more than one category. For example, suppose a left turning driver who has the right of way is hit by an opposing through driver who is charged with running a red light and suffers a broken arm. Based on the criteria used, the crash would be classified in red light running crash, injury crash and injury crash attributable to red light running crash categories.

Table 3.3 Criteria used to Classify Crashes by Examining FR300 Crash Report Form

Category	Criteria Based on Examining the FR300 Crash Report Form
Total Crashes	Includes all the crashes within 150 feet of the intersection
Total Injury Crashes	Includes all the crashes within 150 feet of the intersection with injury count equal or more than one.
Crash not related to red light nor red light running	• The crash did not occur at the intersection (i.e. signal) in question • Both drivers claim to have had the green light and no independent witnesses are available • Both drivers had a green light, and one failed to yield right of way • No charges are filed due to conflicting statements • A rear-end crash occurred, and the description states that the front car was stopped due to traffic • A rear-end crash occurred, and the description states that the rear car could not stop due to mechanical failure • A rear-end crash occurred, and the rear driver had a medical emergency • The crash involves one vehicle, a vehicle and an animal or fixed object, or a vehicle and a pedestrian or bicyclist, unless box 17 or 18 is coded as a 21 (which indicates the driver disregarded stop-go light, as shown in Appendix C) • In a rear-end crash, both vehicles were stopped at a red light, and the rear car accidentally let off the brake or the rear car accelerated too quickly after the light turned green • There is no crash, and a car has mechanical failure or catches fire Note: Any crashes that meet these criteria may not be included in the following categories
Rear-end crash attributable to a red light	• A rear-end crash occurred, and the description states that the front car was stopped due to a red light • The front car was stopped at red light and the rear car did not stop • The rear car claimed to be braking for a yellow or red light, and could not stop (even if driver could not stop due to wet pavement Note: Rear-end crashes are often coded in box 17 or 18 as #12 (Following too closely), #23 (Driver Inattention), or #37 (with "Failure to maintain control" note) in Fairfax County.
Crash attributable to red light running	• Either box 17 or 18 (or both) have the code 21 (the driver "disregarded stop-go light") • Either box 17 or 18 have the code 34 (Hit and Run), and the description states one of the cars ran the red light • For some reason, neither box 17 nor 18 are coded 21, but the description clearly states that one of the cars ran the red light • Note that in Fairfax County, almost all of these crashes were angle crashes.
Injury crash attributable to red light running	If a crash attributable to red light running as classified above results in at least one an injury.

One should be careful while comparing the crashes i.e. the critical decision is to be consistent and to avoid a comparison of different crash types such as comparing *total injury crashes at one location to injury crashes attributable to the red light running at* *another location.* Appendix C shows part of the FR300 template that is relevant to understanding the codes described in Table 3.3.

It should be noted here that the accurate classification of crashes is one of the most important factor influencing the accuracy of a safety evaluation study and it is believed that higher accuracy was obtained in the study by classifying the crashes using FR300 narrative and diagram. The study experience showed that crash narrative is one of most important element of a FR300 form to classify the crashes. For example, in the FR300 form there is a field where the police officer writes down the offenses charged to the drivers. If one of the drivers is charged with "disregarded stop-go light", one can be sure that the crash involved red light running and can be attributed to red light running. However, during data extraction it was observed that for a number of cases the crash narrative written by police officer showed clear indication that the crash happened due to red light running whereas the driver was charged with offenses other than "disregarded stop-go light". The reason for this is that sometimes when a driver commits more than one violation, the driver is charged with the offense that takes precedence over the others. For example, in a hit and run case, the driver who ran away is always charged with hit and run offense irrespective of the other offenses he might have committed because the hit and run offense has the precedence over other charges. Thus examination of the "driver action" only on FR300 does not guarantee that one will capture all red light running crashes. It is clear that one should use his or her discretion before classifying the crashes based on the way it has been coded in the FR300 for a meaningful research. At least, a small subset of the data should be checked with the FR300 narrative to be sure about the accuracy of the dataset.

Traffic Engineering Data

Traffic engineering data for Fairfax and Prince William counties such as average daily traffic (ADT), percentage of heavy trucks and the yellow signal timings were obtained from various sources.

Average daily traffic (ADT)

Average daily traffic data for major road of the intersection were obtained from count books and the traffic counts available from the VDOT Traffic Engineering Division internal website. Full intersection volumes i.e. major road and minor road ADT were desirable, however due to unavailability of the minor road ADT from the sources the ADTs were obtained for major road of the intersections. At a few intersections where the aforementioned sources cannot provide the data, jurisdiction officials were asked to provide the data. The ADT ranged from 17,000 vehicles per day to 81,000 vehicles per day for the Fairfax County sites.

Truck Percentages

Percentages of trucks (trucks with six or more tires) in the major road traffic stream at the intersections were obtained from the VDOT count books. It included 2-axle, 3-axle, 1-trailer and 2-trailer trucks and didn't include buses. For the study sites in Fairfax County, the truck percentages ranged from 0% to 9%. The volume data and the truck percentages were collected for the same major approach of the intersection.

Yellow Interval

Durations of the yellow intervals at the traffic signals were obtained from VDOT district and central office staff. The data was provided in the form of Synchro files and the Excel files. Yellow interval in excess of ITE recommended yellow interval was considered in the study instead of absolute yellow interval and was calculated as:

Yellow interval difference at the major road defined as:

ITE yellow difference = Existing yellow interval + Grace period (0.2 sec for Fairfax County) – ITE recommended yellow interval

While calculating the ITE recommended yellow interval, the grade at the intersection approaches was assumed to be zero as the grade data for all the intersections was not available at the time when the study was undertaken. For the Fairfax County dataset, the ITE yellow difference was between -0.1 sec and 1.8 sec.

Speed Data

Posted speed limit data were also obtained from previous reports, such as an analysis conducted by BMI for VDOT (BMI, 2003). Although approach speed data would have been preferable, approach speeds were not available for most intersections; hence, posted speed limit data were used. For the study sites in Fairfax County, the speed limits ranged from 35 mph to 55 mph. As no change in the speed limits was reported during the study period i.e. from year 1998 to year 2003, it was assumed that the speed limits remained constant during the study period.

Number of Lanes

The numbers of left turn lanes and through lanes on major road were also obtained for the intersections through various sources. These sources included published reports (e.g. BMI report), FR300s, and signal-timing files used in the Synchro simulation package.

3.4. Analysis

Safety impacts were assessed by analyzing citation data and crash data. This had three components:

1. A simple before after comparison: to determine how photo red enforcement is affecting the citations.

Two methods of crash analysis were used.

2. Empirical Bayes method: to determine impact of cameras on crashes.
3. Analysis of Variance (ANOVA) and Generalized Linear Models (GLM) based method: to study how the safety impact of cameras compares to that of confounding factors (such as average daily traffic, yellow interval and intersection geometry) and to pinpoint locations where use of photo-red enforcement can have beneficial safety effect. (ANOVA was used as a screening tool to delineate the factors (including interaction terms) that potentially affect the crash frequency, and GLM was used to model those factors terms to know how these factors were affecting the crash frequency.)

Each of the above components is described in detail in the following sections of the thesis.

4. CITATION ANALYSIS

Reliable citation data were successfully obtained from four jurisdictions: Alexandria, Arlington, Fairfax County, and Vienna. Changes in the citation rate and in the citation pattern were studied. As mentioned earlier, citations data reflect the number of citations mailed out (i.e., the number of actual violations), not the number of events where a vehicle was photographed.

4.1. Changes in Citation Rate

To evaluate the impact of camera enforcement on citations rate, a 3-month stabilization period was considered and the number of citations in the 4th, 5th, and 6th months after camera installation were compared with the number of citations during the most recent 3 months of operation.

At some intersections in Fairfax County, the yellow interval was changed after installation of the cameras. In those cases, a period with a constant yellow interval was considered. For example, the intersection of Route 7 and Dranesville Road had a camera installed in July 2001 and then had its yellow interval changed in March 2003. The total number of citations sent in October 2001, November 2001, and December 2001 were compared with the total number of citations sent in December 2002, January 2003, and February 2003. For the other jurisdictions of Alexandria, Arlington, and Vienna, yellow timing information was not used in the creation of Table 4.1.

Table 4.1 summarizes these results for each intersection and each jurisdiction. Thus, for the Route 7 and Dranesville Road intersection, the number of citations from October 2001 through December 2001 (1,007) is compared to the number of citations from December 2002 through February 2003 (752), which yields a 25% reduction for this period when the yellow interval did not change. For the other jurisdictions of Alexandria, Arlington, and Vienna, yellow timing information was not used in the creation of Table 4.1.

Overall, most intersections showed a net reduction in citations: this was the case for 10 of the 12 Fairfax County intersections, 1 of the 2 Vienna intersections, 2 of the 3 Alexandria intersections, and 4 of the 5 Arlington intersections. By jurisdiction, the average reductions in intersection citations were 46% (Alexandria), 12% (Arlington), and 19% (Fairfax County), with a 7% increase in Vienna.

The comparisons for Fairfax County are based on periods with a constant yellow interval. When the periods are expanded to include changes in the yellow interval, it is logical that changes in the yellow interval would further affect the number of citations. Figures 4.1, 4.2, and 4.3 graph the number of citations at three Fairfax County intersections after the installation of cameras. In Figures 4.1 and 4.2, the yellow interval was increased in March 2003, whereas in Figure 4.3 the yellow interval remained constant. Each graph shows the citations data after the installation of the cameras only as there was no automated system in place to capture all the violations in the before period.

Table 4.1 Impact of Cameras on Number of Citations in Different Jurisdictions

Intersection	Month (Early Period)			Month (Later Period)			Percentage Reduction
	4th	5th	6th	3rd most recent	2nd most recent	1st most recent	
Alexandria							
Patrick & Gibbon Street	1047	1205	878	306	351	388	67
Seminary and Nottingham	589	616	533	101	141	166	77
Duke St and Walker St.	408	238	566	472	589	212	-5
Average Reduction for Alexandria							46
Arlington							
Rt. 50 @Fillmore St.	103	56	654	29	19	28	91
Rt. 50 @ Manchester St.	292	284	319	868	950	619	-172
Wilson @ Lynn St.	1249	1322	1650	783	906	646	45
Lynn St. @ Lee Hwy.	340	355	333	147	138	84	64
Jeff Davis Hwy @ S 27th St.	880	818	811	498	500	688	33
Average Reduction for Arlington							12
Fairfax County							
Fairfax County Pkwy and Newington Rd	370	253	353	282	217	173	31
Fairfax County Pkwy and Popes Head Rd	495	442	486	397	329	287	29
Little River Tnpk and Heritage Drive	115	119	152	101	107	74	27
Route 28 and Old Mill	547	274	182	180	165	119	54
Route 50 and Fair Ridge Dr[a]	16	23	7	30	21	8	-28
Route 50 and Jaguar Trail	365	465	397	346	341	238	25
Route 50 and Rugby Rd	197	231	85	113	194	196	2
Route 7 and Dranesville Rd	285	372	350	314	219	219	25
Route 7 and Route 66	448	510	395	264	296	312	36
Route 7 and Westpark Drive	286	170	156	244	215	234	-13
Telegraph Rd and Huntington Ave	193	174	163	160	177	158	7
Route 7 and Carlin Spring Rd	200	145	212	149	138	89	32
Average Reduction for Fairfax County							19
Vienna							
Maple Av E/Follin Lane	466	518	343	283	336	320	29
Maple Av E/Nutley St.	33	53	64	76	69	68	-42
Average Reduction for Vienna							-7
Average Reduction for all four jurisdictions (each intersection carries equal weight)	19						
Average Reduction for all four jurisdictions (each citation carries equal weight)							33

[a]Because the number of citations for Route 50 & Fair Ridge Drive is quite small relative to the other intersections in Fairfax County, this increase may be an anomaly.

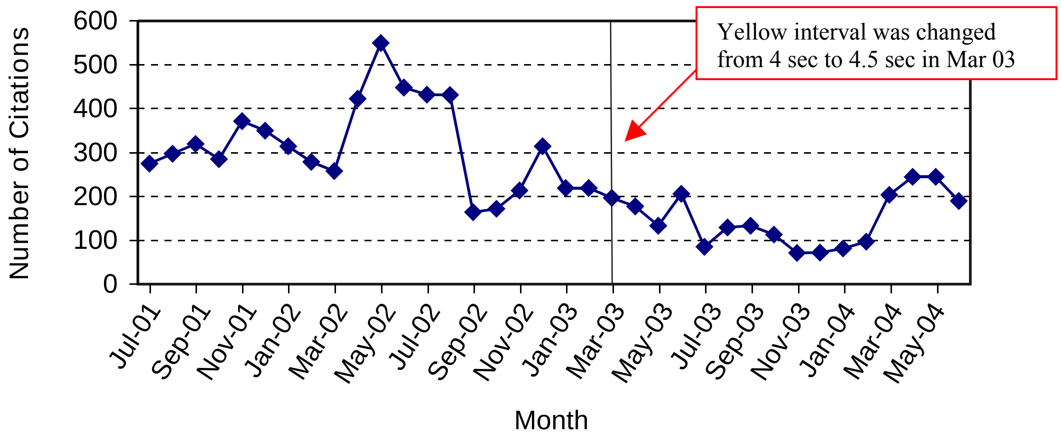

Figure 4.1 Changes in Number of Citations at Route 7 and Dranesville Road (Yellow interval changed in March 2003)

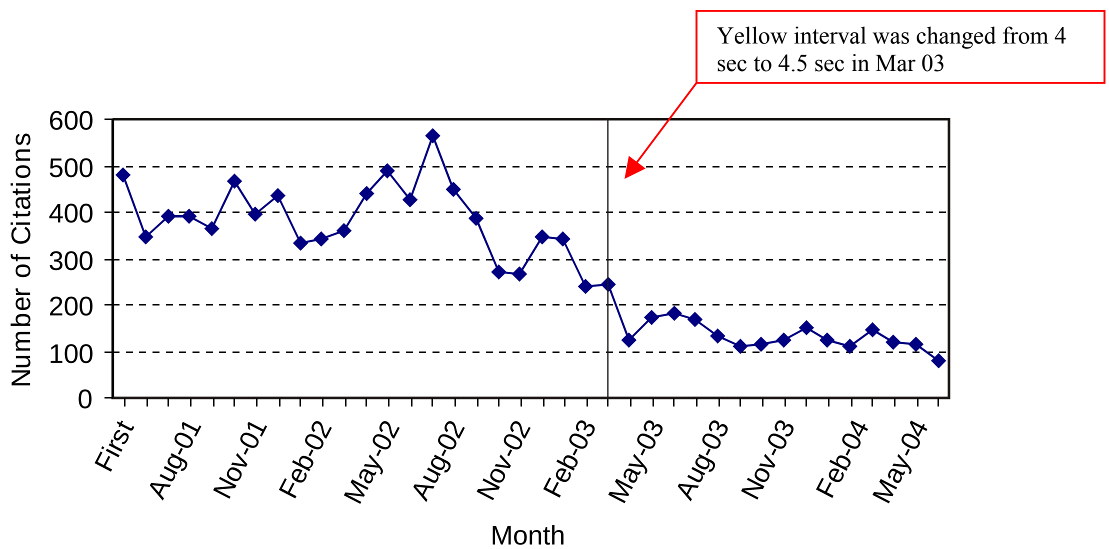

Figure 4.2 Changes in Number of Citations at Route 50 and Jaguar Trail (Yellow interval changed in March 2003)

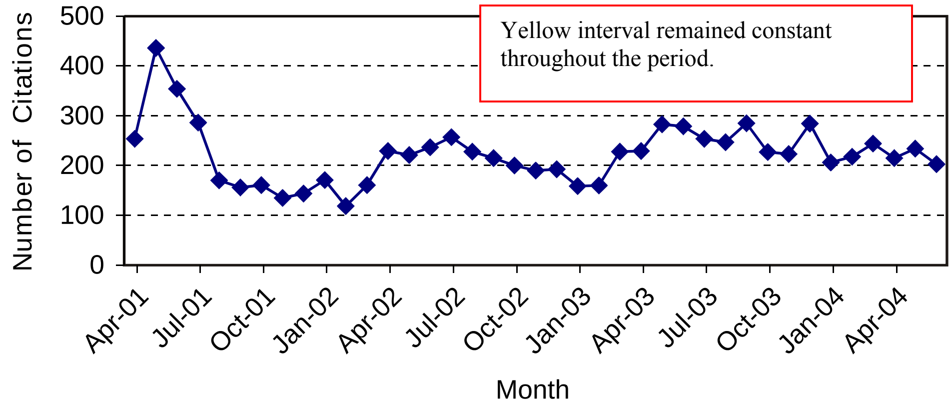

Figure 4.3 Changes in Number of Citations at Route 7 and Westpark Drive

4.2. Changes in Citation Pattern

The *time into the red* is another relevant feature of the citations: after the signal turns red, at what point do most of the citations occur? Table 4.2 shows how the *85th percentile time into the red* changed at the various traffic signals. For example, the first row of Table 4.2 shows that for the Patrick and Gibbon Street intersection in Alexandria, 85% of all citations occurred within 1.30 seconds of the signal changing to red in the 3 early months of the signal's operation. In the 3 most recent months, however, that 85th percentile time had increased slightly; in the most recent month, 85% of citations occurred with 1.50 seconds of the signal changing to red. For that particular signal, therefore, the difference between the earlier and later periods is positive, reflecting that in the later period, the citations were occurring later into the red than in the earlier period.

Table 4.2. Impact of Cameras on 85th Percentile time in Red (seconds)

Intersection	Month (Early Period) 4th	5th	6th	Month (Later Period) 3rd most recent	2nd most recent	1st most recent	Difference
Alexandria							
Patrick & Gibbon Street	1.30	1.30	1.30	1.30	1.40	1.50	0.10
Seminary & Nottingham	1.30	1.30	1.30	1.20	1.30	1.10	-0.10
Duke St & Walker St.	1.30	1.40	1.40	1.60	1.60	1.64	0.25
Arlington							
Rt. 50 @Fillmore St.	1.20	1.20	1.50	1.80	0.93	1.30	0.04
Rt. 50 @ Manchester St.	1.10	1.00	0.93	1.60	1.60	1.60	0.59
Wilson @ Lynn St.	1.80	1.70	2.06	1.10	1.20	1.10	-0.72[a]
Lynn St. @ Lee Hwy.	1.30	1.20	1.30	1.42	1.90	1.46	0.33
Jeff Davis Hwy @ S 27th St.	1.00	1.00	1.00	0.90	1.00	1.00	-0.03
Fairfax County							
Fairfax County Pkwy & Newington Rd	1.40	1.50	1.50	1.20	1.10	0.93	-0.39
Fairfax County Pkwy & Popes Head Rd	1.00	1.10	1.00	1.10	1.00	1.00	0.00
Little River Tnpk & Heritage Drive	0.80	0.80	1.10	0.93	0.90	0.89	0.00
Route 28 & Old Mill	1.00	0.82	1.00	1.00	1.00	0.90	0.03
Route 50 & Fair Ridge Dr	1.81	1.09	1.73	2.44	1.89	0.91	0.21
Route 50 & Jaguar Trail	1.00	1.00	1.00	1.20	1.00	1.06	0.09
Route 50 & Rugby Rd	1.10	1.10	1.10	1.00	1.00	1.00	-0.10
Route 7 & Dranesville Rd	1.20	1.00	1.10	1.00	1.00	1.00	-0.10
Route 7 & Route 66	1.20	1.10	1.10	1.20	1.40	1.00	0.07
Route 7 & Westpark Drive	1.00	1.10	1.10	1.10	1.02	0.98	-0.03
Telegraph Rd & Huntington Ave	1.30	1.30	1.20	1.30	2.86	2.51	0.96[c]
Route 7 & Carlin Spring Rd	0.93	0.90	0.80	0.90	0.90	1.06	0.08
Vienna							
Maple Av E/Follin Lane	1.97	2.04	2.24	1.43	1.41	1.57	-0.61
Maple Av E/Nutley St.	0.98	1.06	2.71	1.82	1.25	1.88	0.06[b]

[a]Because this signal showed the greatest reduction in the 85th percentile time into the red, its citation history is shown in Figure 4.4.
[b]Because this signal showed little change in the 85th percentile time into the red, its citation history is shown in Figure 4.5.
[c]Because this signal showed the greatest increase in the 85th percentile time into the red, its citation history is shown in Figure 4.6.

Because the 85th percentile time into the red does not describe the entire citation history, Figures 4.4, 4.5, and 4.6 show the distribution, for the later periods, of time into the red at three signals. Figure 4.4 shows the time into the red for the Arlington signal at Wilson and Lynn Street, which had showed the greatest reduction in 85th percentile time into the red in Table 4.2. Similarly, Figures 4.5 shows a citation history for a signal that had little change in the 85th percentile time into the red, and Figure 4.6 shows a citation history for the signal with the greatest increase for 85th percentile time into the red.

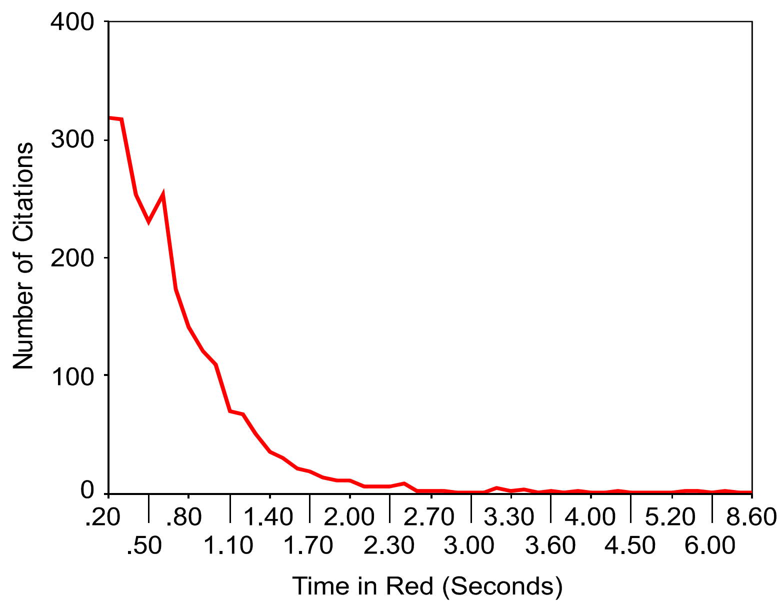

Figure 4.4 Citation History at Wilson/Lynn St, Arlington (This is the signal with the greatest reduction in 85th percentile time into the red.

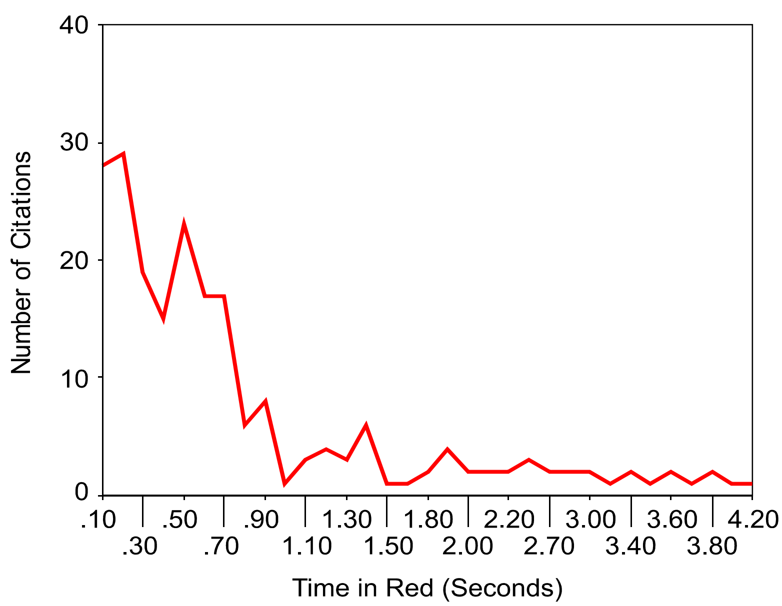

Figure 4.5 Citation History at Maple Ave E/Nutley St, Town of Vienna (This is the signal with little change in 85th percentile time into the red)

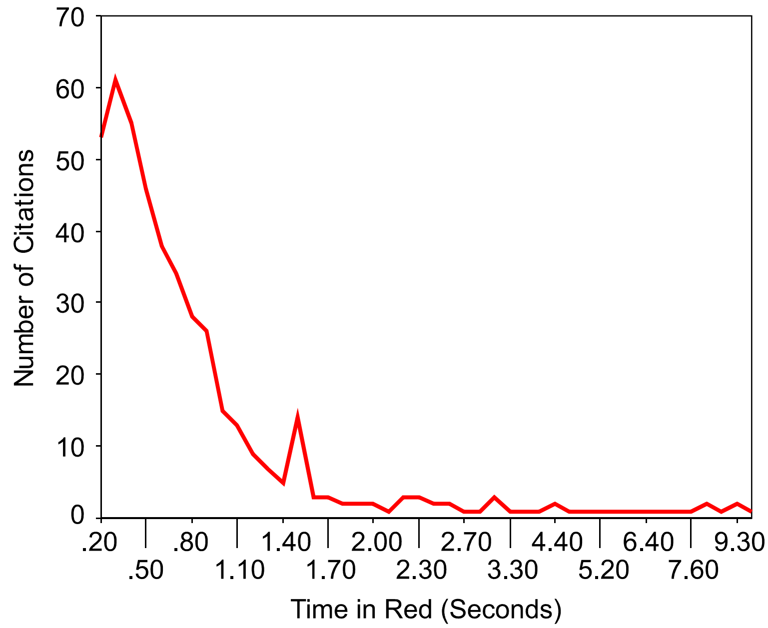

Figure 4.6 Citation History at Telegraph Rd/Huntington Ave, Fairfax County (This is the signal with the greatest increase in 85th percentile time into the red)

Table 4.2 shows that 85th percentile time ranges between 0.8 to 2.86 seconds when both early and later periods are considered. If the most recent period 85th percentile times are examined, 14 intersections out of 22 intersections have 85th percentile time within 1.1 seconds indicating that 85 percent of total citations are happening within a short period of 1.1 seconds at most of the intersections. At these intersections, one may expect to have safety benefit in terms of reduced violations by increasing the yellow interval slightly (up to 1 second). However, the increase should not be high enough to tempt motorists to speed up to cross the intersections. Further, there is no apparent pattern between the percentage reduction in citations (from Table 4.1) and the change in 85th percentile time into the red (from Table 4.2 or Figures 4.4, 4.5, and 4.6). These types of figures may be appropriate for future study, however, to examine crashes more closely at specific signals with driver citation patterns.

5. EMPIRICAL BAYES METHOD: IMPACT OF CAMERA ON CRASHES

5.1. Empirical Bayes Methodology

The Empirical Bayes (EB) method was used to analyze the available crash data for Fairfax County. EB method is a rigorous method to estimate the safety impact attributable to the treatment and has been widely used in various traffic safety studies in recent past. Further, the EB method has been well documented at several references that provide a step by step overview of how to apply the EB method (Garber et al., 2003, Hauer, 1997). The EB method increases precision in safety estimation by correcting for regression to mean bias that arises because of non-random selection of treatment entities. (For example, the cameras are generally placed at locations with higher number of crashes.) In brief, estimated number of crashes at an intersection that would have occurred without a treatment was compared with actual crashes in the after period to determine safety impact of the treatment. The method is summarized as three steps:

Step 1: Determine the crash estimation model (CEM). A multivariate regression model of the following form is developed to estimate the mean of the expected crash frequency $E(k_{i,j})$ at an intersection site (*i*) in a particular year (*j*):

$$E(k_{i,j}) = \alpha_y \times x_1^{b_1} \times x_2^{b_2} \times x_3^{b_3} \times ..... \qquad \text{(Eq.5.1)}$$

where

x_1, x_2, x_3 . . . are independent variables such as major road AADT, number of lanes on major road, etc.

b_1, b_2, b_3 . . . are model parameters of the independent variables x_1, x_2, x_3 . . ., respectively.

At a site, there may be other factors that could affect the crash frequency but the effect of which is either not known or not explicitly modeled in the equation. Such factors may include weather, economic conditions, vehicle technologies, and changes in driver behavior. The effects of these factors are represented as α_y in the model (see Eq. 5.1), which represent yearly changes. The multivariate model parameters are estimated using the maximum log likelihood method.

Step 2: Compare the actual crashes to those predicted by the CEM. Once the sets of traits for a treated site (say site *i*) for the before years 1, 2, 3 . . . *n* are known, the regression estimate $E(k_{i,j})$ for 1, 2, 3 . . . *n* years is calculated from Eq.5.1. This regression estimate is combined with the accident history of the site $K_{i,1}, K_{i,2}, K_{i,3}, K_{i,4} ......K_{i,n}$ for the before years to estimate the expected number of accidents, i.e., $k_{i,1}, k_{i,2}, k_{i,3}, k_{i,4} ....k_{i,n}$, and their variance $Var(k_{i,1}), Var(k_{i,2}), Var(k_{i,3}), Var(k_{i,4}) ....Var(k_{i,n})$ using the following five equations (Garber et al., 2003, Hauer, 1997).

$$C_{i,y} = \frac{E(k_{i,y})}{E(k_{i,1})} \qquad \text{(Eq. 5.2)}$$

$$k_{i,1} = \frac{k + \sum_{y=1}^{n} K_{i,y}}{\frac{k}{E(k_{i,1})} + \sum_{y=1}^{n} C_{i,y}} \quad \text{(Eq. 5.3)}$$

k (k is the dispersion parameter that is different from $k_{i,y}$) is determined from the calibration process of the model and essentially reflects the type of crash distribution in the model.

$$Var(k_{i,1}) = \frac{k + \sum_{y=1}^{n} K_{i,y}}{(\frac{k}{E(k_{i,1})} + \sum_{y=1}^{n} C_{i,y})^2} = \frac{k_{i,1}}{\frac{k}{E(k_{i,1})} + \sum_{y=1}^{n} C_{i,y}} \quad \text{(Eq. 5.4)}$$

$$k_{i,y} = C_{i,y} k_{i,1} \quad \text{(Eq. 5.5)}$$

$$Var(k_{i,y}) = (C_{i,y})^2 Var(k_{i,1}) \quad \text{(Eq. 5.6)}$$

The after period *would have been crash frequency* $k_{i,n+1}, k_{i,n+2}, k_{i,n+3}, \ldots k_{i,n+z}$ is calculated using Eq. 5.7. The after period extends from year *n*+1 to year *n*+*z*.

$$k_{i,y} = C_{i,y} k_{i,1} \quad \text{(Eq.5.7)}$$

where

$$C_{i,y} = \frac{E(k_{i,y})}{E(k_{i,1})} \text{ and } y = n+1, n+2\ldots, n+z$$

Here, to clarify, $k_{i,n+1}, k_{i,n+2}, k_{i,n+3}, \ldots k_{i,n+z}$ are estimates of the number of crashes that would have occurred in the after years had the treatment not been implemented.

Step 3: Statistically compare the expected crashes from the CEM to the actual number of crashes that did occur.

The effect of the treatment is estimated by comparing the "would have been" crashes with actual crashes in the after period. The "would have been crashes" at each site *i* during the after period are denoted as $\pi_{i,}$ and the actual crashes at each site during the after period are denoted as λ_i. Equations 5.8 and 5.9 are used to sum the crashes from the individual sites as π and λ.

$$\pi = \sum_i \pi_i \qquad \text{(Eq. 5.8)}$$

$$\lambda = \sum_i \lambda_i \qquad \text{(Eq. 5.9)}$$

The index of effectiveness (θ) is used as a measure of safety and is defined in Eq. 5.10 as a ratio of ratio of actual to "would have been" crashes. A value of θ less than 1.0 indicates that the treatment improved safety. However, the unbiased estimator of θ is given by Eq. 5.11. Eqs. 5.12 and 5.13 show the variance and confidence bounds, respectively.

$$\theta = \lambda/\pi(\text{“actual crashes” divided by “would have been” crashes}) \qquad \text{(Eq. 5.10)}$$

$$\theta = (\lambda/\pi)/\{1+\mathrm{Var}(\pi)/\pi^2\} \qquad \text{(Eq. 5.11)}$$

$$\mathrm{Var}(\theta)=\theta^2\{[\mathrm{var}(\lambda)/\lambda^2]+[\ \mathrm{var}(\pi)/\pi^2]\}/[1+\ \mathrm{var}(\pi)/\pi^2]^2 \qquad \text{(Eq. 5.12)}$$

$$\theta \pm [2\mathrm{Var}(\theta)]^{0.5} \qquad \text{(Eq. 5.13)}$$

The confidence bounds, shown in Eq. 5.13 are used to determine whether the value for θ shows a statistically significant safety impact. If the confidence bounds for θ contain 1.0, then the safety impact computed by Eq. 5.13 is not significant; thus, one cannot say that the treatment had a measurable effect.

Critical Assumptions for Using the Formulation of CEM

The multivariate model parameters are estimated using the maximum log likelihood method. The log likelihood function is built upon a few assumptions, which are necessary to gain insight into the Empirical Bayes framework. There are two critical assumptions for using the formulation of CEM.

Assumption 1: In a given year, the expected number of crashes in a population of sites follows a Gamma distribution. For example, suppose in year 1998 there are 30 different intersection sites. Further imagine that all other factors (driver behavior, vehicle technologies, traffic volumes, geometric characteristics) are identical. Because crashes are probabilistic phenomena, there will be some random variation in the number of crashes. For any given year, the distribution of crashes by sites will follow the Gamma distribution. Finally, it is unrealistic to assume that 30 sites will be identical as per the first assumption. Because it is probably impossible to obtain a physical population to support these assumptions, literature refers to them as an "imagined reference population".

If the expected number of accidents on a site *i* in year *j* is denoted by $k_{i,j}$ then $k_{1,1}, k_{2,1}, k_{3,1} .....k_{r,1}$ are Gamma distributed with mean $\mathrm{E}(k_{i,1})$. The $k_{i,j}$ values vary within this imagined reference population, as there are differences among the sites due to the other traits that haven't been taken into account in the equation. Thus, $k_{1,1}, k_{2,1}, k_{3,1} .....k_{r,1}$ are realizations from an imagined reference population and are Gamma distributed.

Assumption 2: Count of accidents (K) at a particular site for a particular year obeys Poisson probability law with mean equal to $k_{i,j}$. Thus once we know $k_{i,j}$, we can calculate the probability of happening of 0, 1,2..…n accidents at the site. It should be emphasized that we have only one realization of the Poisson distribution at a particular site in a particular year.

The above two assumption are further explained in the Figure 5.1.

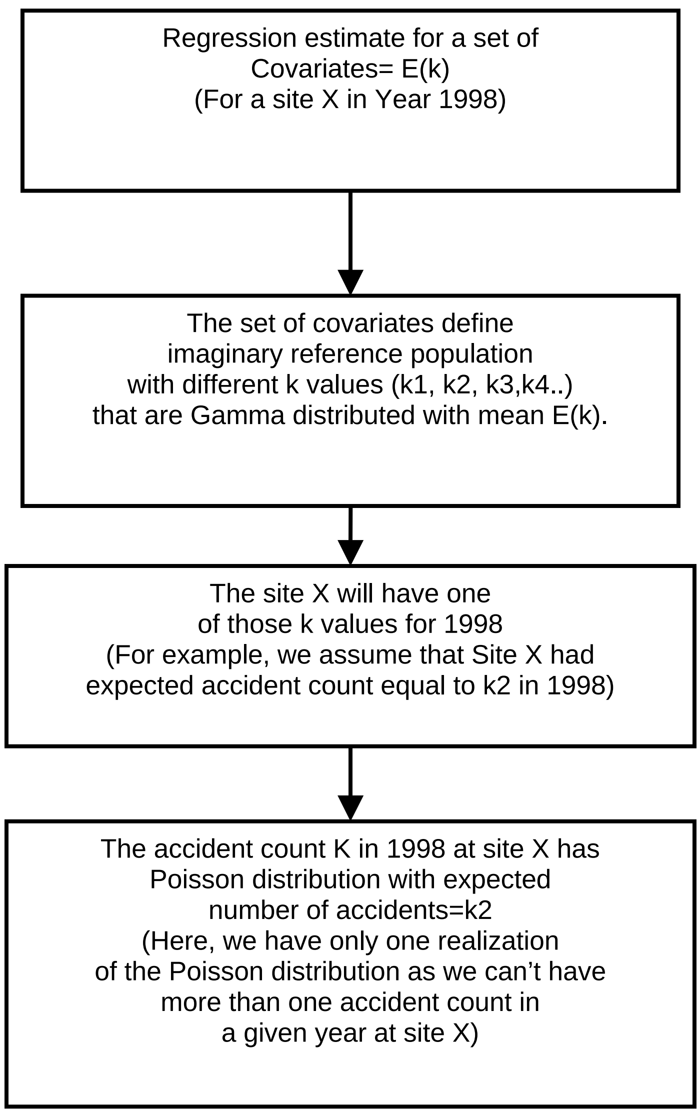

Figure 5.1: Assumptions in Crash Estimation Models

5.2. Results of Analysis

Crash Estimation Model

CEMs were required to estimate the mean of the expected number of crashes. The independent variables were selected primarily based on two criteria: (1) their ability to explain the variation in crash frequency and (2) the availability of the data. Eq. 5.14 gives the form of the crash estimation model used to estimate the mean of the expected number of crashes on a particular site for all five types of crashes examined.

$$Crashes / Year = \alpha_y (ADT)^b (Speed)^c (YellowDiff)^d (Trucks)^e (Lanes)^f \quad \text{(Eq. 5.14)}$$

where

b, *c*, *d*, *e*, *f* and α_y are model parameters.

ADT, *Speed*, *YellowDiff*, *Trucks,* and *Lanes* are independent variables as described in Table 1.

Table 5.1 Variables Used in Crash Estimation Models

Variable	Description
ADT	Average daily traffic on the major road (17,000 to 78,000 vehicles/day)
Lanes	Number of through lanes for a single approach of the major road or sum of the number of left turn lanes on both approaches of the major road
Speed	Posted speed limit at the major road (35, 40, 45, 50, or 55 mph)
YellowDiff	Yellow interval difference at the major road is defined as: YellowDiff= Existing yellow interval+ Grace period (0.2 sec) – ITE recommended yellow interval (between 0.1 sec and 1.8 sec)
Truck	Percentage of trucks present in traffic stream on major road (between 1% and 9 %)

The models for different crash types were calibrated using data obtained for a group of reference sites in Fairfax County. The model parameters were estimated using a customized spreadsheet application developed by the Virginia Transportation Research Council. The spreadsheet employs the methodology described by (Hauer, 1997) for the development of the CEMs and was validated using different datasets before it was used to develop the models for this study. The spreadsheet requires initial values of the parameters as input and as an output gives optimized parameter values that maximize the log likelihood function. It was observed that different initial values of the parameters could produce different set of optimized parameters values that may fit the data. The reason was that the likelihood function value produced local maximum instead of the global maximum. For this, a trial method with variations in initial parameter values was used and a set of optimized parameter values that produced highest of the log likelihood function values of those trials was chosen. The highest log likelihood function value of those trails thus chosen has high probability of being close to global maximum; however, it may not be the global maximum.

One of the problems was that the volume data were missing for a few years for a few sites. To manage the 33 missing volume data values out of a total 276 volume data values, a sensitivity analysis was conducted with following options summarized in Table 5.2.

Table 5.2 Different Options to Tackle the Missing Data

Situation	Option	Description
Site where most of the years do not have volume data (e.g., volumes are available for years 1 and 2 but missing for years 3, 4, 5, and 6)	A	Estimate an average volume (based on years 1 and 2) and use that average volume for years 3, 4, 5, and 6
	B	Discard the site entirely
Site where most of the years do have volume data (e.g., volumes are available for years 2, 3, 4, 5, and 6 but missing for year 1)	C	Choose the minimum value of years 2, 3, 4, 5, and 6 as the volume for year 1
	D	Choose the maximum value of years 2, 3, 4, 5, and 6 as the volume for year 1

Accordingly, four different scenarios were defined to test the results using the analysis options shown in the above table:

Scenario 1:	analysis options A and C
Scenario 2:	analysis options A and D
Scenario 3:	analysis options B and C
Scenario 4:	analysis options B and D

As explained later, the uncertainty in volumes did not affect the conclusion drawn regarding the sign of the impact on crashes. Also, analysis was done separately for through lanes and left turn lanes as one of the independent variables of the crash estimation models to examine if the results were different. Thus, there were total 8 scenarios for each crash type (4 volume scenarios with left lanes and 4 volume scenarios with through lanes). The crash estimation model parameters and confidence interval for index of effectiveness for the different scenarios for each crash type are given in Table 5.3 and Table 5.4. Table 5.3 shows the estimated parameters when sum of the number of left lanes in both directions on major approach was used as one of the independent variables in the CEM. Table 5.4 shows the estimated parameters when the number of through lanes in one direction on major approach was used as one of the independent variables in the CEM.

Table 5.3 Summary of Empirical Bayes Results for Fairfax County Crashes with Left Lanes as One of the Independent Variables

Crash Type[a]	Scenario	Exponents: Volume (b)	Exponents: Speed Limit (c)	Exponents: Yellow (d)	Exponents: Trucks (e)	Through Lanes (f)	α_{1998}	α_{1999}	α_{2000}	α_{2001}	α_{2002}	α_{2003}	Confidence interval for the reduction in crashes	
Total crashes	1	0.101	0.000	0.392	0.170	0.061	4.243	4.183	4.299	4.372	3.943	4.519	1.11	1.13
	2	0.117	0.000	0.392	0.169	0.061	3.590	3.542	3.634	3.694	3.331	3.817	1.11	1.13
	3	0.059	0.000	0.398	0.140	0.000	7.005	7.042	7.418	7.630	6.931	7.819	1.08	1.09
	4	0.100	0.000	0.397	0.136	0.000	4.562	4.591	4.808	4.936	4.488	5.059	1.08	1.09
Total injury crashes	1	0.447	0.000	0.402	0.138	0.059	0.040	0.041	0.043	0.038	0.040	0.040	1.16	1.2
	2	0.449	0.000	0.407	0.141	0.059	0.039	0.040	0.042	0.038	0.039	0.039	1.16	1.2
	3	0.439	0.000	0.556	0.110	0.000	0.048	0.052	0.055	0.049	0.052	0.050	1.1	1.13
	4	0.453	0.000	0.482	0.053	0.000	0.043	0.046	0.048	0.043	0.046	0.042	1.12	1.15
Injury Crashes Attributable to red light running	1	0.397	0.000	0.472	0.000	1.381	0.004	0.003	0.004	0.003	0.003	0.004	0.67	0.77
	2	0.440	0.376	0.498	0.000	1.351	0.001	0.001	0.001	0.000	0.000	0.001	0.67	0.77
	3	0.438	0.142	0.504	0.142	0.091	0.004	0.004	0.004	0.003	0.003	0.005	0.66	0.76
	4	0.429	0.231	0.520	0.129	0.072	0.003	0.003	0.004	0.002	0.003	0.004	0.66	0.76
Rear-end crash related to red light	1	0.544	0.100	0.433	0.175	0.159	0.005	0.005	0.005	0.006	0.005	0.005	1.53	1.6
	2	0.540	0.000	0.433	0.179	0.167	0.008	0.008	0.008	0.009	0.007	0.008	1.58	1.65
	3	0.401	0.000	0.386	0.109	0.441	0.031	0.030	0.031	0.036	0.029	0.031	1.52	1.58
	4	0.389	0.100	0.419	0.099	0.684	0.020	0.019	0.020	0.023	0.019	0.020	1.47	1.53
Crash attributable to red light running	1	0.150	0.422	0.686	0.022	0.000	0.101	0.086	0.096	0.091	0.057	0.085	0.69	0.75
	2	0.184	0.392	0.682	0.020	0.000	0.079	0.067	0.075	0.071	0.044	0.066	0.69	0.75
	3	0.099	0.438	0.727	0.039	0.000	0.150	0.136	0.158	0.142	0.088	0.142	0.67	0.72
	4	0.144	0.393	0.721	0.034	0.000	0.111	0.101	0.116	0.105	0.065	0.105	0.66	0.71

[a]Please see Table 3.3 for precise definitions of crashes.

Table 5.4 Summary of Empirical Bayes Results for Fairfax County Crashes with Through Lanes as One of the Independent Variables

		Exponents											Confidence interval for the reduction in crashes	
Crash Type[a]	Scenario	Volume (b)	Speed Limit (c)	Yellow (d)	Trucks (e)	Through Lanes (f)	α_{1998}	α_{1999}	α_{2000}	α_{2001}	α_{2002}	α_{2003}		
Total crashes	1	0.095	0.000	0.394	0.166	0.423	3.119	3.078	3.166	3.220	2.902	3.319	1.09	1.1
	2	0.113	0.000	0.394	0.165	0.433	2.557	2.525	2.592	2.634	2.374	2.714	1.09	1.1
	3	0.051	0.000	0.399	0.136	0.506	4.672	4.698	4.955	5.098	4.629	5.208	1.05	1.06
	4	0.069	0.000	0.399	0.134	0.504	3.888	3.912	4.116	4.232	3.844	4.322	1.05	1.06
Total injury crashes	1	0.439	0.002	0.538	0.143	0.001	0.047	0.048	0.050	0.045	0.047	0.047	1.09	1.13
	2	0.430	0.005	0.573	0.160	0.000	0.051	0.053	0.055	0.050	0.051	0.052	1.08	1.12
	3	0.429	0.000	0.611	0.179	0.001	0.049	0.054	0.057	0.051	0.055	0.054	1.04	1.07
	4	0.426	0.001	0.622	0.195	0.000	0.049	0.054	0.058	0.051	0.055	0.055	1.04	1.07
Injury Crashes Attributable to red light running	1	0.377	0.000	0.441	0.121	0.000	0.016	0.014	0.016	0.012	0.012	0.017	0.66	0.77
	2	0.429	0.033	0.470	0.073	0.000	0.009	0.008	0.008	0.006	0.006	0.009	0.66	0.76
	3	0.409	0.001	0.513	0.076	0.000	0.011	0.011	0.012	0.008	0.009	0.013	0.66	0.77
	4	0.432	0.001	0.515	0.065	0.000	0.009	0.009	0.010	0.006	0.007	0.010	0.66	0.76
Rear-end crash related to red light	1	0.382	0.000	0.475	0.175	1.418	0.012	0.012	0.012	0.013	0.010	0.012	1.52	1.59
	2	0.386	0.000	0.479	0.175	1.432	0.011	0.011	0.011	0.012	0.010	0.011	1.52	1.58
	3	0.390	0.000	0.462	0.089	1.581	0.010	0.010	0.010	0.012	0.010	0.010	1.45	1.51
	4	0.396	0.000	0.465	0.089	1.584	0.010	0.009	0.010	0.011	0.009	0.010	1.45	1.51
Crash attributable to red light running	1	0.142	0.302	0.672	0.000	0.478	0.111	0.093	0.105	0.099	0.062	0.091	0.68	0.73
	2	0.173	0.274	0.669	0.000	0.467	0.089	0.075	0.084	0.080	0.049	0.074	0.68	0.73
	3	0.098	0.366	0.711	0.004	0.413	0.140	0.125	0.146	0.131	0.081	0.129	0.66	0.71
	4	0.140	0.329	0.706	0.000	0.402	0.103	0.093	0.107	0.097	0.060	0.095	0.66	0.71

[a]Please see Table 3.3 for precise definitions of crashes.

CEM parameters did not differ by more than a few percentage points in each scenario. For the sake of consistency, therefore, the results of one scenario, where missing volume data is estimated by using option A and option C (see Table 5.2) and number of left lanes was used as one of the independent variables in CEM, are discussed in this section. This scenario is referred as Scenario 1 in the rest of the chapter.

Table 5.5 gives the estimated parameters for the five crash models developed for Scenario1.

Table 5.5 Crash Estimation Model Parameters for Scenario 1

Parameter	Total Crashes (Sum of All Crashes at Intersection)	Total Injury Crashes	Injury Crashes Attributable to Red Light Running	Rear-End Crashes	Crash Attributable to Red Light Running
Volume (b)	0.101	0.447	0.397	0.544	0.150
Speed Limit (c)	0.000	0.000	0.000	0.100	0.422
YellowDiff (d)	0.392	0.402	0.472	0.433	0.686
Trucks (e)	0.170	0.138	0.000	0.175	0.022
Left Turn Lanes (f)	0.061	0.059	1.381	0.159	0.000
α_{1998}	4.243	0.040	0.004	0.005	0.101
α_{1999}	4.183	0.041	0.003	0.005	0.086
α_{2000}	4.299	0.043	0.004	0.005	0.096
α_{2001}	4.372	0.038	0.003	0.006	0.091
α_{2002}	3.943	0.040	0.003	0.005	0.057
α_{2003}	4.519	0.040	0.004	0.005	0.085
k	1.77	1.90	1.97	1.59	1.89

Safety Effect of Red Light Cameras (Scenario 1)

Table 5.6 shows the actual crash counts and the estimated number of crashes in the after period had there been no treatment. For example, there were 58 crashes at the Leesburg Pike and Dranesville Road intersection in the after period and the EB estimate of the "would have been crashes" in the after period had there been no treatment was 51.7 (see Table 5.6). For all 13 camera intersections combined, the actual total crash count and the estimated number of total crashes in the after period had there been no treatment were 551 and 491.9, respectively. These numbers indicate that the cameras were causing a 12% increase in the total crashes overall at these 13 intersections.

Table 5.6 Actual and Predicted Crash Counts at Individual Intersection (Scenario 1)

	Actual Crash Count in After Period					Estimated Number of Crashes in After Period (Had There Been No Treatment)				
	λ					π				
Intersection	Total Crashes	Total Injury Crashes	Rear-end	Red light running	Injury red light running	Total crashes	Total injury crashes	Rear-end	Red light running	Injury red light running
Leesburg Pike, Dranesville Road	58	25	14	9	5	51.7	17.3	17.9	5.6	3.2
Leesburg Pike, Towlston Road	31	12	9	1	0	10.4	5.2	0.8	1.3	1
Leesburg Pike, Westpark Drive	115	34	40	6	1	80.7	28.2	23.7	7.2	3.4
Leesburg Pike, Route 66	44	18	15	10	5	42.3	14	12.4	5.1	2.6
Arlington Boulevard, Jaguar Trail	67	21	30	3	2	65.6	24.2	17.3	9.9	4.2
Route 7, Carlin Springs Rd	13	6	4	0	0	18.4	7	2.6	1.8	1
Telegraph Road, Huntington Avenue	49	22	14	6	3	46.8	15.6	7.5	6.6	3.3
Route 236, Heritage Drive	34	10	21	0	0	30.7	8.1	6	3.3	0.9
Fairfax County Pkwy, Newington Road	1	0	0	0	0	4.9	1.8	2.1	1.6	0.8
Fairfax County Pkwy, Popes Head Road	23	13	14	0	0	23.9	11.1	5.4	2.7	1.8
Lee Jackson Mem Hwy, Rugby Road	58	17	24	7	4	46.2	19.4	17.4	6.5	4.7
Lee Jackson Mem Hwy, Fair Ridge Dr	31	12	14	3	3	55.6	21.3	21.3	8.7	4.3
Route 28, Greens Trail Boulevard	27	16	16	0	0	14.7	1	2.3	2	0.5
Overall Group	551	206	215	45	23	491.9	174.1	136.9	62.3	31.7

Estimates of the index of effectiveness for the different crash types for the overall group of 13 treated intersections are given in Table 5.7. As shown, the confidence interval for index of effectiveness (θ) for total crashes lies between 1.11 and 1.13. Thus, as summarized in Table 5.8, the cameras are correlated with an increase in total crashes ranging between 11% and 13%. Similarly, the confidence interval for index of effectiveness (θ) for red light running crashes lies between 0.75 and 0.69, indicating that the cameras are correlated with a decrease in red light running crashes and the decrease ranges between 25% and 31%. Likewise, the cameras are correlated with a decrease in injury crashes attributable to red light running (between 23% and 33%), an increase in rear-end crashes (between 53% and 60%), and an increase in total injury crashes (between 16% and 20%) as shown.

Table 5.7 Estimates of Safety Effect for All Intersections (Scenario 1)

Crash Type	Actual Crash Count in After Period	Estimated Number of Crashes in After Period (Had There Been No Treatment)	Index of Effectiveness (θ)	Variance of Index of Effectiveness (Var (θ))	Empirical Confidence Interval	
	$\Sigma\lambda_I$	$\Sigma\pi_I$	$(\lambda/\pi)/[1+VAR(\pi)/\pi^2]$	$\theta^2\{[VAR(\lambda)/\lambda^2]+VAR(\pi)/\pi^2]\} / [1+VAR(\pi)/\pi^2]^2$	$\theta \pm 2VAR(\theta)^{0.5}$	
Total	491.9	551.0	1.12	0.00	1.13	1.11
Total Injury	206.0	174.1	1.18	0.01	1.20	1.16
Rear-end	215.0	136.9	1.57	0.02	1.60	1.53
Red light running	45.0	62.3	0.72	0.01	0.75	0.69
Injury red light running	23.0	31.7	0.72	0.03	0.77	0.67

Table 5.8 Empirical Bayes Estimation of Impact on Crashes (Scenario 1 Only)

Crash Type	Impact on Crashes	Range
Total crashes (sum of all crashes at the intersection)	Increase	11% to 13%
Total injury crashes	Increase	16% to 20%
Injury crashes attributable to red light running	Decrease	23% to 33%
Rear-end crashes	Increase	53% to 60%
Crashes attributable to red light running	Decrease	25% to 31%

Results Based on All Scenarios

For the case of rear end crashes, the four scenarios in Table 5.3 suggest θ values between 1.47 and 1.65, and the four scenarios in Table 5.4 suggest θ values of 1.45 to 1.59. This suggests an overall range of θ (index of effectiveness) between 1.45 and 1.65; thus, rear end crashes increased by a value between 45% and 65%. Similarly for the other crash types, overall range is found out using Table 5.3 and Table 5.4. These results suggest the following:

- The cameras are correlated with an increase in total crashes of 5% to 13%.
- The cameras are correlated with an increase in rear-end crashes related to the presence of a red light; the increase ranges between 45% and 65%.
- The cameras are correlated with a decrease in crashes attributable to red light running, and the decrease is between 25% and 34%.
- The cameras are correlated with a decrease in injury crashes attributable to red light running, with the decrease being between 23% and 34%.
- The cameras are correlated with an increase in total injury crashes, with the increase being between 4% and 20%.

Note that the uncertainty in volumes did not affect the conclusion drawn regarding the sign of the impact on crashes. For example, all scenarios show that the cameras decrease red light running crashes. The scenarios do affect the magnitude of this impact. For example, red light running crashes decreased by 25% to 31% (scenario 1 in Table 5.3) or 29% to 34% (scenario 4 in Table 5.3).

5.3. Observations

A few observations follow from the EB results.

1. The alpha value obtained for the crash estimation model for year 2002 was generally less than other years. The different alpha values for different years are attributed to the change in the way factors, which are not modeled explicitly in CEM, affect the crash occurrence. The relative different alpha value in 2002 suggests that there may be some non-captured changes that are particularly reducing the number of crashes in 2002.
2. The estimated parameters for the speed limit variable were either statistically insignificant or zero. The posted speed limits were used instead of the actual operational speeds and thus actual operational speeds, instead of posted speed limits, are necessary to determine if speeds had an impact on crash frequency.
3. For each CEM, there is an inverse relationship between the alpha values (for year) and the exponents for the independent variables (e.g. yellow interval, ADT, et cetera). This suggests that amount of explanatory power contained within traffic engineering and geometric factors, varies by year.

6. ANALYSIS OF VARIANCE AND GENERALIZED LINEAR MODELS BASED APPROACH

The EB method described in the previous chapter examined the impact of cameras on the crashes. However, two critical questions remain that directly impact the utility of these cameras:

1) How does the safety impact of cameras compare to other factors such as intersections geometry, average daily traffic and yellow interval?
2) What are the ideal locations for these cameras? Although literature on best practices is available to put the cameras, however, there has not been quantitative research done to identify the candidate locations where safety benefits can be achieved by installing cameras.

To answer both of the above questions, analysis of variance (ANOVA) and generalized linear models (GLM) based approach were explored. ANOVA was used as a screening tool to delineate the factors (including interaction terms) that potentially affect the crash frequency, and GLM was used to model those factors to examine how these factors were affecting the crash frequency.

6.1. ANOVA Methodology

ANOVA is a statistical methodology in which total variation in a measured response is partitioned into components, which can be attributed to recognizable sources of variation. ANOVA's strength is that it allows one to control for confounding factors, which was accomplished through two iterations shown in Table 6.1. In both cases, main and second order interaction effects were considered. The first iteration used data collected at all 13 camera intersections and 33 comparison intersections (without camera) for a total of 46 Fairfax County intersections. A single *site* variable was used to represent all *geometric characteristics*. Statistically, therefore, each site functioned as a block in this analysis.

Table 6.2 summarizes the variables used in this first iteration. In the second ANOVA iteration the single *site* variable was replaced with six *geometric* variables as shown in Table 6.3. The second ANOVA analysis was done to identify which geometric characteristics, in lieu of, *site* variable were affecting the crash frequency. The variables shown in Table 6.2 and Table 6.3 were used as categorical variables.

Table 6.1: Variables Considered in ANOVA Tests

Test	Variable Considered
First ANOVA analysis (46 Sites)	Traffic characteristics (see Table 6.2) and a single site variable representing geometric characteristics of each intersection site
Second ANOVA analysis (32 Sites)	Traffic characteristics (Table 6.2) and the single site variable replaced with multiple variables each of which represents a specific geometric characteristic (Table 6.3)

Table 6.2: Variables Used in the First ANOVA Analysis (With a Single *Site* Variable)

Variable Name	Description
Traffic Characteristics (Collected for 46 sites)	
Camera	Camera at intersection (1 = yes, 0=no)
Average Daily Traffic	Average daily traffic on the major road (17,000 to 78,000 vehicles/day)
ITE Diff	Yellow interval difference at the major road defined as: ITEDiff = Existing yellow interval+ Grace period (0.2 sec) – ITE recommended yellow interval (-0.1 sec to 1.8 sec)
Truck %	Percentage of trucks present in traffic stream on major road (between 1% and 9%)
Site	1 for site 1, 2 for site 2… and 46 for site 46

Table 6.3: *Geometric* Data Replacing the *Site* Variable in the Second ANOVA Analysis

Variable Name	Description
Number of Through lanes	Sum of the number of through lanes present in the both directions of the major road (ranged between - 4 to 8)
Number of Left lanes	Sum of the number of left turn lanes present in the both directions of the major road (ranged between - 1 to 4)
T intersection	T intersection or not (1=yes, 0=no)
Curb Cuts	Total number of legs of the intersection with curb cuts
Speed Limit**	Posted speed limit at the major road (35, 40, 45, 50, 55 mph)
Frontage Road	Frontage road present or not (1=yes, 0=no)

**Because speed limit represents the constant posted speed limit (not the actual traffic operational speed), it is treated as a geometric characteristic of the sites.

The rationale for the two ANOVA analyses is that they delineate the factors that potentially affect the crash frequency. These factors can be broadly classified into three different categories: *human characteristics, traffic characteristics,* and *geometric characteristics*. As the data reflected a single county only, one can assume that the human factors within that county do not vary significantly across sites. Traffic characteristics are represented by ADT, truck percentages, and yellow interval differences, which have already been included in the first ANOVA analysis. Therefore, it can be assumed that most of the explanatory power of the *site* variable in the first ANOVA analysis is probably due to variation in the *geometric* characteristics across the sites.

To verify whether the sites have geometric differences, aerial images of intersections were scrutinized, and it was found that the sites had significant geometric differences that could affect the crash experience. Consider for example the Van Dorn and Franconia Road intersection (Figure 6.1): a four-legged intersection with no frontage road and no curb cuts. By contrast, consider the Route 236 and Heritage Drive intersection (Figure 6.2). Clearly the frontage roads and curb cuts present in Figure 6.2 differentiate that intersection from that shown in Figure 6.1. These differences illustrate the utility of the six *geometric* variables shown in Table 6.3.

Of the 46 sites, five had no corresponding aerial images, which precluded collection of geometric data. Further, nine sites appeared to have fundamentally different characteristics not explicitly captured by Table 6.3, such as sharp curvature, the existence of a one-way street or parking lots, construction during the study period, or other irregular geometry. Therefore, a total of 14 sites were excluded such that the second ANOVA iteration was done with only 32 rather than 46 sites. The amount of variation explained by each model, reflected by its adjusted R^2 defined in Eq. 6.1 was used to compare the performance of the two models (Hogg & Ledolter, 1992).

$$\text{Adjusted } R^2 = 1 - \frac{(Errror\ Sum\ of\ Squares)/(n-p-1)}{(Total\ Sum\ of\ Squares)/(n-1)} \qquad \text{(Eq.6.1)}$$

Where, n = number of obersevations

p = number of explanatory variables

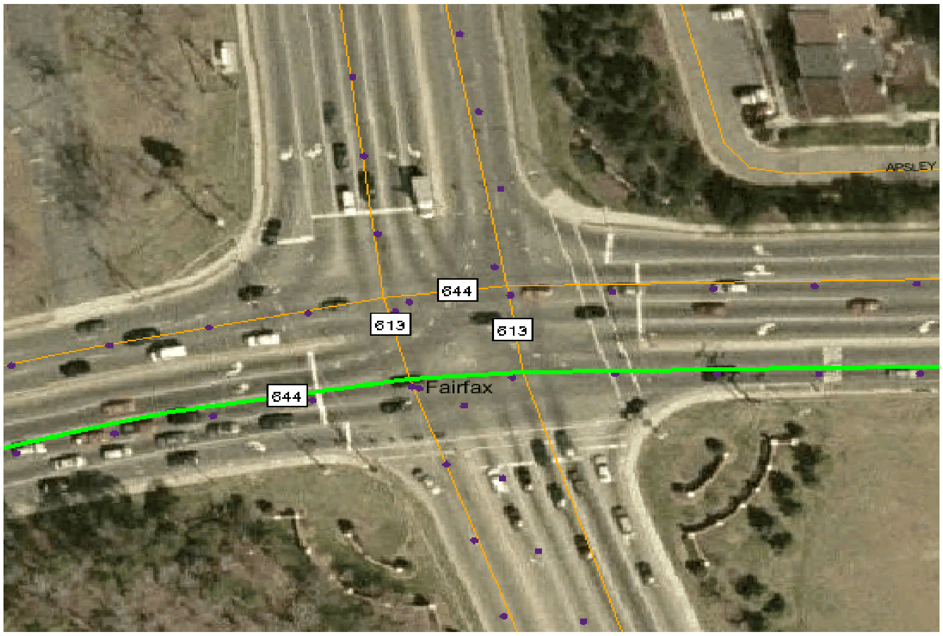

Figure 6.1: Van Dorn and Franconia Rd intersection in Fairfax County

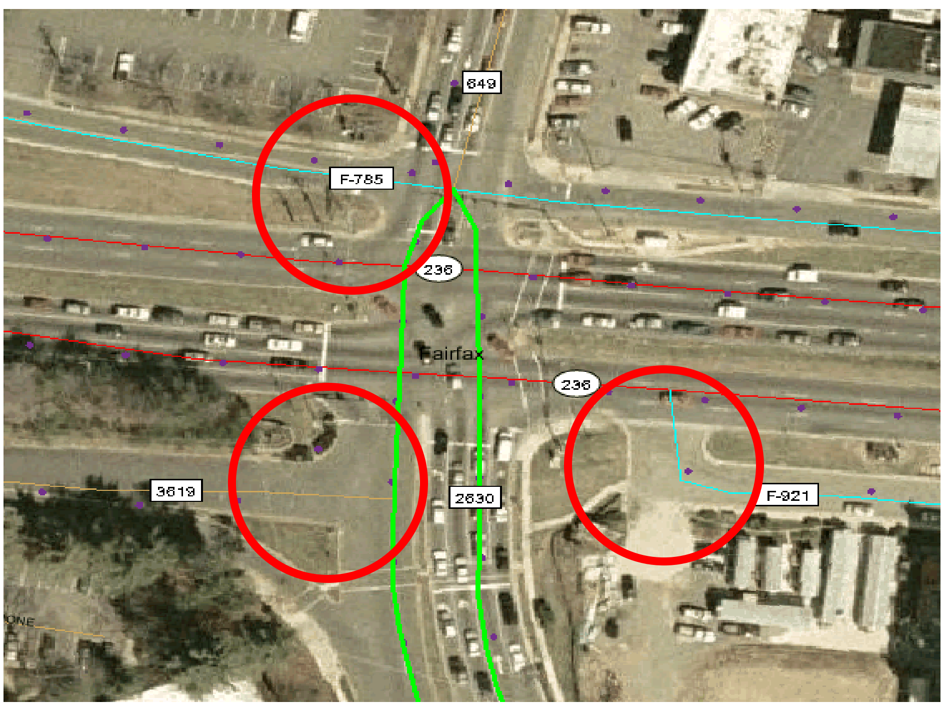

Figure 6.2: Route 236 and Heritage Dr intersection in Fairfax County

6.2. ANOVA Results

The results of the first ANOVA analysis are shown in Table 6.4. The site variable is highly significant for all crash types. In most cases, the other main effects and interaction effects were insignificant. Exceptions, however, were Camera effect (rear end crashes), the interaction effect of ADT and ITE difference (for total crashes and rear end crashes) and the interaction effect of Camera and ADT (for rear end crashes).

By themselves, the first ANOVA analysis results confirm the previous simple before after study analysis in that the main effects of the camera influence rear end crashes ($p = 0.003$) and probably influence red light running crashes ($p = 0.065$). The results of this first ANOVA test are not very useful because they do not specify which characteristics inherent in the site variable explain the variation in crash frequency and do not provide adequate information about the characteristics of a site that may be more conducive to camera being effective.

The results of the second ANOVA analysis using traffic data as well as geometric data for 32 sites are shown in Table 6.5.

Table 6.4: Results of First ANOVA Analysis: *p* values

	Total Crashes	Rear End Crashes	Red Light Running Crashes	Red Light Running Injury Crashes	Total injury crashes
SITE	0.000*	0.000*	0.000*	0.000*	0.000*
CAMERA	0.438	0.003*	0.065	0.175	0.227
ADT	0.490	0.662	0.817	0.485	0.885
ITEDIFF	0.413	0.939	0.656	0.587	0.588
TRUCK	0.195	0.153	0.319	0.703	0.065
CAMERA * ADT	0.502	0.012*	0.459	0.577	0.177
CAMERA *ITEDIFF	0.532	0.537	0.229	0.478	0.479
CAMERA * TRUCK	0.795	0.413	0.714	0.923	0.281
ADT * ITEDIFF	0.002*	0.002*	0.064	0.399	0.080
ADT * TRUCK	0.650	0.562	0.305	0.504	0.788
ITEDIFF * TRUCK	0.908	0.376	0.942	0.575	0.879
Adjusted R^2	0.8	0.654	0.382	0.3	0.623

* Shows the variables significant at 5% significance level

Table 6.5: Results of Second ANOVA Test: *p* values

	Total Crashes	Rear End Crashes	Red Light Running Crashes	Red Light Running Injury Crashes	Total Injury Crashes
CAMERA	0.015*	0.000*	0.497	0.416	0.084
ADT	0.221	0.129	0.803	0.849	0.614
FRONTAGE	0.214	0.089	0.288	0.953	0.567
CURBCUTS	0.063	0.385	0.731	0.209	0.030*
THRULANE	0.000*	0.026*	0.291	0.076	0.000*
LEFTLANE	0.000*	0.008*	0.204	0.144	0.000*
ITEDIFF	0.000*	0.002*	0.902	0.685	0.008*
TRUCK	0.114	0.169	0.352	0.052	0.131
CAMERA* CURBCUTS	0.810	0.743	0.672	0.783	0.756
CAMERA * ITEDIFF	0.028*	0.078	0.074	0.064	0.291
CAMERA * TRUCK	0.289	0.345	0.892	0.860	0.190
ADT * CURBCUTS	0.301	0.193	0.546	0.386	0.492
ADT * THRULANE	0.118	0.496	0.391	0.551	0.091
ADT * LEFTLANE	0.016*	0.262	0.592	0.893	0.056
ADT * TRUCK	0.487	0.968	0.215	0.058	0.316
SPEEDLMT * TRUCK	0.613	0.940	0.035*	0.021*	0.763
FRONTAGE * TRUCK	0.674	0.294	0.430	0.016*	0.885
CURBCUTS*THRULANE	0.297	0.515	0.679	0.697	0.281
CURBCUTS * TRUCK	0.388	0.600	0.691	0.341	0.757
THRULANE * TRUCK	0.623	0.937	0.700	0.166	0.425
LEFTLANE * TRUCK	0.140	0.234	0.657	0.909	0.059
ITEDIFF * TRUCK	0.078	0.953	0.198	0.740	0.325
Adjusted R^2	0.742	0.664	0.339	0.404	0.613

*Shows the variables significant at 5% significance level

Table 6.5 showed comparable adjusted R^2 values for all crash types. This finding proves the feasibility of using distinct geometric characteristics to describe the physical differences between sites. That is, in Table 6.4, the single *site* variable meant there were 46 categories of intersections – one for each location. Table 6.5, however shows that it is now possible to have a smaller number of categories. For example, in our data set, four intersections with 45 mph posted speed limit, two through lane per major approach and one left turn lane per major approach were placed in one category (as per Table 6.5) rather than four different categories (as per Table 6.4).

Table 6.5 shows that the presence of the camera has a statistically significant impact on rear end crashes, which is in accord with Table 6.4. Table 6.5 also shows that camera presence has a significant impact on the total crashes and that yellow interval difference significantly affects total crashes, rear end crashes and total injury crashes. (These effects were not significant in the first ANOVA analysis as shown in Table 6.4.) The camera impact is significant for total crashes and rear end crashes.

The geometric variables also significantly influenced crash frequency. The number of through lanes and number of left turn lanes significantly impact total crashes, rear end crashes and total injury crashes. Most second order effects were insignificant. Exceptions include Camera*ITEDiff and ADT*LeftLane (for total crashes), SpeedLimit*Truck (for red light running crashes and injury crashes related to red light running), and Frontage*Truck percentage (for injury crashes related to red light running).

Clearly the use of 32 sites with explicit geometric characteristics as shown in Table 6.5 offered greater explanatory power. Variables not significant in Table 6.4, such as the difference between ITE yellow interval and actual yellow interval, were found to be significant in Table 6.5. These results illustrate that the sites had distinct geometric characteristics and it is important to explicitly model these characteristics in the analysis for a correct analysis.

6.3. Generalized Linear Model (GLM) Methodology

Thus ANOVA analysis was helpful in delineating the factors that affect the crash frequency at a site. The two-tier ANOVA analysis helped in understanding the utility of selecting a relatively homogenous group of sites and explicitly modeling their distinct geometric characteristics. A linear equation for each crash type can be developed with crash type as dependent variable and first order main effect terms and second order interaction terms as dependent variables to quantify the effect of each variable on the frequency of crashes. However, the linear model thus developed assumes normally distributed error structure. This assumption has been criticized in the literature and is not correct (Hadayaghi et al, 2003, Lord et al, 2005). Recent research has shown that the population of interest herein—crashes—is not normally distributed but rather follows either the Poisson or Negative Binomial distribution (Lord et al., 2005). Therefore, the Poisson and Negative Binomial distribution based GLMs, which are more appropriate for modeling discrete and discontinuous crash data were explored.

A brief introduction to the GLMs is given in Appendix F.

GLM Estimation

In exploring the GLMs, all first order effects and second order effects that were significant at 5% level in ANOVA analysis were used. Thus, ANOVA was used as a screening tool for the estimation of generalized linear models. Traffic data and geometric data of the 32 sites (used in second ANOVA iteration) were used for estimation of the models. The regression coefficients of the explanatory variables were estimated by the Log Likelihood method using the statistical package SAS. The decision whether to keep a variable in the model was based on whether the *p* value was less than or equal to 0.05. Since one of the main objectives of the research was to determine the impact of cameras on different crash types, the camera variable was forced in the model even if its estimated parameter was not significant at a 5% level.

The goodness of fit of the models was tested using statistic called mean Pearson Chi Square estimate (defined as the Pearson Chi Square divided by the degrees of freedom). Both Poisson models and Negative Binomial models were developed, however NB models were chosen because of the acceptable fit of the models: the dispersion parameter values were different from zero as they should be and the mean Pearson Chi Square estimate lies between 0.8 and 1.2 (Hadayaghi et al., 2003).

Table 6.6: Negative Binomial Estimation of Intersection Crashes

Total Crashes				
Parameter	Estimate	Std Error	Chi-Square	Pr > ChiSq
Intercept	0.4014 (a)	1.4503	0.08	0.782
Camera	0.6167 (b_1)	0.1994	9.56	0.002
LnADT	0.3044 (b_2)	0.1391	4.79	0.0287
ITEDiff	0.5727 (b_3)	0.1085	27.87	<.0001
SpeedLimit	-0.0467 (b_4)	0.0097	23.01	<.0001
ThruLanes	0.1582 (b_5)	0.0348	20.65	<.0001
CurbCuts	-0.1728 (b_6)	0.0551	9.84	0.0017
Camera*ITEDiff	-0.7331 (b_7)	0.2544	8.3	0.004
Dispersion	0.1827	0.0273		
Rear End Crashes				
Parameter	Estimate	Std Error	Chi-Square	Pr > ChiSq
Intercept	-7.5939 (a)	2.044	13.8	0.0002
Camera	1.4214 (b_1)	0.2593	30.05	<.0001
LnADT	0.5869 (b_2)	0.195	9.06	0.0026
ITEDiff	0.5863 (b_3)	0.1436	16.67	<.0001
ThruLanes	0.3069 (b_4)	0.0526	34.05	<.0001
LeftLanes	0.1752 (b_5)	0.0847	4.28	0.0386
Camera*ITEDiff	-0.7532 (b_6)	0.3193	5.57	0.0183
Dispersion	0.2619	0.063		
Total Injury Crashes				
Parameter	Estimate	Std Error	Chi-Square	Pr > ChiSq
Intercept	-2.9826 (a)	1.607	3.44	0.0635
Camera	0.2119 (b_1)	0.1396	2.3	0.1291
LnADT	0.4085 (b_2)	0.163	6.28	0.0122
SpeedLimit	-0.0262 (b_3)	0.0101	6.73	0.0095
ITEDiff	0.2529 (b_4)	0.1138	4.94	0.0262
ThruLanes	0.2366 (b_5)	0.0394	35.99	<.0001
Dispersion	0.1787	0.0382		
Total Red Light Running Crashes				
Parameter	Estimate	Std Error	Chi-Square	Pr > ChiSq
Intercept	-1.3248 (a)	0.4034	10.78	0.001
Camera	-0.8056 (b_1)	0.3035	7.05	0.0079
ThruLanes	0.3137 (b_2)	0.0682	21.16	<.0001
TInterSection	-1.1256 (b_3)	0.4244	7.03	0.008
FrontageRoad	0.7052 (b_4)	0.2194	10.33	0.0013
Dispersion	0.5185	0.135		
Injury Crashes Related to Red Light Running				
Parameter	Estimate	Std Error	Chi-Square	Pr > ChiSq
Intercept	-2.5141 (a)	0.4989	25.4	<.0001
Camera	-0.6641 (b_1)	0.34	3.82	0.0508
ThruLanes	0.3955 (b_2)	0.0813	23.66	<.0001
TInterSection	-1.1723 (b_3)	0.529	4.91	0.0267
FrontageRoad	0.6351 (b_4)	0.2283	7.74	0.0054
Dispersion	0.1984	0.1375		

Table 6.6 shows the estimated parameters of the model, based on the Negative Binomial distribution, for the five crash categories.

6.4. GLM Results

Based on the results shown in the Table 6.6 following equations can be produced for crash estimation.

$$TotalCrashes^{1} = Exp(0.40 + 0.62Camera + 0.30LnADT + 0.57ITEDiff - 0.05SpeedLimit + 0.16ThruLanes - 0.17CurbCuts - 0.73Camera * ITEDiff) \quad \text{(Eq. 6.2)}$$

$$RearEndCrashes^{1} = Exp(-7.59 + 1.42Camera + 0.59LnADT + 0.59ITEDiff + 0.31ThruLanes - 0.18LeftLanes - 0.75Camera * ITEDiff) \quad \text{(Eq. 6.3)}$$

$$TotalInjuryCrashes^{1} = Exp(-2.98 + 0.21Camera + 0.41LnADT + 0.25ITEDiff - 0.03SpeedLimit + 0.24ThruLanes) \quad \text{(Eq. 6.4)}$$

$$TotalRLRCrashes^{1} = Exp(-1.32 - 0.81Camera + 0.31ThruLanes - 1.13Tintersection + 0.71FrontageRoad) \quad \text{(Eq. 6.5)}$$

$$TotalInjuryCrashes^{1} = Exp(-2.51 - 0.66Camera + 0.4ThruLanes - 1.17Tintersection + 0.64FrontageRoad) \quad \text{(Eq. 6.6)}$$

Note 1: The right hand of side of each equation (Eq. 6.2 to Eq 6.6) gives the mean number of crashes per year. The probability density function of number of crashes a year (y_i) is given by

$$f(y_i) = \frac{\Gamma(y_i + 1/k)}{\Gamma(y_i + 1)\Gamma(1/k)} \frac{(k\mu_i)^{y_i}}{(1 + k\mu_i)^{y_i + 1/k}} \quad \text{for} \quad y_i = 0, 1, 2, \ldots \qquad \text{(Eq. 6.7)}$$

Where k is dispersion parameter and is given in Table 6.6 for each crash type. Thus, if the characteristics of the intersection (the independent variables in an equation) are given, the mean number of different crash types per year can be calculated by using Eq. 6.2-6.6. Once the mean number of crashes is calculated, the probability of obtaining crashes equal to 0, 1, 2...etc can be calculated by using Eq. 6.7. (The subscript *i* represents a set of independent variables values for which the mean number of crashes are obtained from any of the equations from Eq.6.2 to Eq.6.6, depending on the crash type of interest, and than the whole distribution is obtained from Eq. 6.7 using that mean value by calculating the probabilities of getting crash counts equal to $y_i = 0, 1, 2, \ldots$etc.)

The results show that cameras are correlated with a significant increase in total crashes, an insignificant increase in total injury crashes, a significant increase in rear end crashes, a significant decrease in red light running crashes, and a significant decrease in injury crashes related to red light running. The results of a simple correlation analysis between camera variable and different crash types as shown in Table 6.7 also showed consistent signs. The cameras presence was correlated with increase in total crashes, total injury crashes and rear end crashes. The camera presence was correlated with decrease in red light running crashes and injury red light running crashes.

Table 6.7 Correlation analysis: Camera Variable vs. Different Crash Types

		Camera	Rear end	Total Crashes	All Injury Crashes	Injury Red Light Running Crashes	Red Light Running Crashes
Camera	Pearson Correlation	1.00	0.46	0.18	0.13	-0.05	-0.07
	Sig. (2-tailed)		0.00	0.02	0.06	0.45	0.33

For all crash types, the models indicate that intersections with more through lanes tend to have a higher number of crashes. The model also suggests that the total number of crashes and the total number of injury crashes are lower at locations with higher posted speed limits. However, this finding needs to be verified because of three possible limitations. First, speed limits may have been lowered at intersections with higher crash frequency in the past; thus, higher speed limits could be a surrogate for relatively safe intersections. Second, the speed limits used in this study refer only to signalized intersections with speed limits of 35, 40, 45, 50 and 55 mph. (These results cannot be assumed to be valid for sites that have fundamentally different characteristics from those used in this study, such as divided interstate freeways). Third, the speed limits shown herein are not operational speeds and thus do not reflect speed variance (which has been shown to influence crash risk).

The models suggest that crashes increase as the difference in actual yellow interval and ITE recommended yellow interval increases. At most of the intersections, the yellow interval was already in excess of the ITE recommended yellow interval. Thus it is possible that as the yellow interval increases substantially beyond the ITE recommended yellow interval, the tendency of drivers to speed up and cross the intersection before the red phase increases. This study does not prove that such a behavioral change is occurring. However, it is a plausible explanation for why longer yellow intervals (relative to that required by ITE) are correlated with crash increases. The results obtained here are based on Fairfax County dataset where at most of the intersections yellow difference was already in excess of what is recommended by ITE. Thus, the finding doesn't imply that crashes would increase or decrease if yellow interval is less than that required by ITE standards.

Most of the results are therefore intuitive. For example, T-intersections appear to have lesser red light running crash risk than four legged intersections which is reasonable given the reduction in conflict points. Intersections with frontage roads are shown to increase crash risk, which makes sense given that such intersections have more complex vehicle interactions at the signal than intersections without frontage roads. Still, at least one result is counterintuitive. The models suggest that curb cuts reduce total crashes. Given that curb cuts increase the number of conflict points, it is probable that there is some other factor, not considered in this study, which is responsible for the decrease in the crashes at these sites.

The GLMs showed that interactions of geometric and traffic characteristics are critical to understand why crashes are increasing at certain sites. Consider Eq. 6.8, which illustrates the application of GLM equation using the parameters from Table 6.6 for the case of total crashes.

$$\begin{aligned} TotalCrash &= Exp(0.40 + 0.62Camera + 0.30LnADT + 0.57ITEDiff - 0.05SpeedLimit \\ &+ 0.16ThruLanes - 0.17CurbCuts - 0.73Camera * ITEDiff) \end{aligned}$$

(Eq. 6.8)

From Eq. 6.8 it is clear that cameras lead to an increase in total crashes, as does the practice of having a yellow interval in substantial excess of the recommended yellow interval. If one is interested in reducing total crashes, then quantifying the interaction effect of cameras and the difference between recommended and actual yellow interval is absolutely necessary to knowing whether installation of a camera is appropriate. For example, Eq. 6.8 shows that placing a camera at a site where the yellow interval is quite large will have a beneficial effect. Using Eq. 6.8, mean number of total crashes can be estimated for different scenarios as shown in Table 6.8. Table 6.8 indicates that camera would reduce total crashes by about 50%, assuming an ADT of 50,000, a yellow interval that is 1.8 seconds longer than that recommended by ITE, a 35 mph speed limit, three through lanes for each major approach, and no curb cuts. However, suppose the difference in yellow interval had been only 0.2 seconds instead of 1.8 seconds. In that case, installation of a camera would, according to Eq. 6.8, *increase* total crashes by about 50 %.

Table 6.8: Impact of Yellow Difference and Presence of Camera on Crash Frequency

	Camera	No Camera
Low Yellow Difference* (0.2 Sec)	36	23
Higher Yellow Difference* (1.8 Sec)	28	57

*Yellow Difference is defined as:
Existing yellow interval+ Grace period (0.2 sec) – ITE recommended yellow interval (between -0.1 sec and 1.8 sec)

The finding that the camera can help in reducing crashes where yellow interval difference is relatively higher is based on Fairfax County data only. Also, the range of yellow difference was only -0.1 seconds to 1.8 seconds in the Fairfax data which had only one case where yellow difference was negative. Thus, the finding doesn't imply that cameras may not have beneficial impact where yellow interval is less than that required by ITE standards.

6.5. Comparison of EB and GLM Results

Table 6.9: Summary of EB and GLM Results

Crash Type	EB	GLM
Total crashes (Sum of all crashes at the intersection)	Significant Increase	Significant Increase
Total injury crashes	Significant Increase	Insignificant Increase
Rear-end crash related to red light	Significant Increase	Significant Increase
Crash attributable to red light running	Significant Decrease	Significant Decrease
Injury crashes attributable to red light running	Significant Decrease	Significant Decrease

The EB results discussed in previously were similar to results obtained using GLM method as shown in Table 6.9: the cameras are correlated with a definite decrease in crashes directly attributed to red light running, a definite decrease in injury crashes attributed to red light running, and a definite increase in rear-end crashes and a definite increase in total crashes. However, there is a slight difference regarding total injury crashes. While both the EB method and the GLM method show that these increase, the GLM shows these changes as insignificant while the EB method shows them as significant. Because the EB method accounted for yellow interval, intersection geometry, and yearly temporal changes, it is considered to be the more reliable of the two methods in this application.

7. DISCUSSION OF RESULTS

7.1. Safety Effects of Photo-red Enforcement

The main objective of the study was to determine the safety impact of cameras in terms of crashes and citations. Let us first look at these results.

Impact on Citations

The number of citations for red light running issued per month varied substantially by intersection and ranged from 7 (Route 50 and Fair Ridge Drive in Fairfax County) to 1,205 (Patrick and Gibbon Street in Alexandria). Across the 22 intersections in four different jurisdiction where reliable citation data could be obtained, the citations decreased by an average of 21% per intersection. Close observation of the results showed that the most dramatic reductions occurred at the intersections associated with the larger numbers of citations. When the total number of before citations at all 22 intersections was compared with the total number of after citations at these same 22 intersections, the data suggest that the programs reduced net citations by 33%. This reduction reflects the number of citations issued in the most recent 3 months divided by the number of citations issued in the 4th, 5th, and 6th months of operation, thus capturing the longer-term impact of the cameras. The latter months of operation were chosen to capture an early time period when the cameras were stable. Therefore, cameras are definitely reducing the number of citations.

Impact on Crashes

The analysis of Fairfax County crash data suggests that photo-red enforcement is contributing to:

- An increase in total crashes (between 5% and 13%).
- A decrease in the number of crashes attributable to red light running (between 25% and 34%).
- An increase in rear-end crashes (between 45% and 65%).
- A net decrease in injury crashes attributable to red light running (between 23 and 34%).
- And an increase in total injury crashes (between 4% and 20%).

The percentages shown are those obtained from EB analysis. The EB results strongly suggest that the cameras reduce crashes attributable to red light running yet increase rear-end crashes. These findings are similar to those reported elsewhere. It is not unusual that some of the benefit of red light cameras (reduced injury crashes attributable to red light running) is offset somewhat by an increase in rear-end crashes. However, the evidence collected thus far suggests red light cameras are adversely affecting safety because they are correlated with an increase in total injury crashes between 4% and 20% (although this may be offset by the decrease in red light running injury crashes, which may be more severe than other injury crashes).

Three questions thus arise. First, because the crash results presented herein do not measure severity, how does the severity of (eliminated) red light running crashes compare with the severity of (induced) rear-end crashes? Second, why did this study yield a different conclusion than that in the most recent study of red light camera impacts *(Council et al., 2005)*? Third, does this study prove that cameras adversely impact safety?

1. How does the severity of the decreased red light running crashes compare to the severity of the increased rear-end crashes?

Detailed severity data are not currently available for Fairfax county crashes. Crashes were categorized only as injury or non-injury. In the crash database, therefore, the categorization of a rear-end crash with a minor injury would have been identical with that of an angle crash with a life-threatening injury. However, examination of the crash narrative and diagrams showed that almost all Fairfax crashes attributable to red light running were angle crashes. This finding is relevant as angle crashes are generally thought to be more severe than rear-end crashes. For example, a tabulation of intersection crashes in Fairfax County from 1998 through 2003 showed that 40% of the rear-end crashes resulted in an injury whereas 45% of the angle crashes resulted in an injury. Further, as shown in Table 7.1, the proportion of angle crashes in the "other visible injury" category appears to be higher than the proportion of rear-end crashes in the "other visible injury" category. In addition, the number of deaths at the scene associated with angle crashes was greater than the number associated with rear-end crashes. The information in Table 7.1 does not capture injury severity at the desired level of detail, but this limited information suggests that angle crashes may be generally more severe than rear-end crashes.

Table 7.1 Injury Type for Fairfax County Intersection Crashes, 1998–2003

Crash Type	Number of Deaths Before Report Made	Other Visible Injury (e.g., Bruises, Abrasions, Swelling, Lumps)	No Visible Injury But Complaint of Pain or Momentary Unconsciousness
Rear-end	4 (0.03%)	4,868 (40%)	7,244 (60%)
Angle	29 (0.25%)	5,194 (45%)	6,377 (55%)

Because severity was not explicitly studied, such a hypothesis cannot be verified or refuted by this study. The fact that most red light crashes were angle crashes, however, coupled with the data in Table 7.1, suggests that probably eliminated angle crashes are more severe than induced rear-end crashes.

2. Why did this study suggest results that are different from that of previous work?

The reason the conclusions in this study differed from those of the recent comprehensive study by Council et al. *(Council et al., 2005)* is that the increase in Fairfax rear-end crashes at camera sites (45% to 65%) was much larger than that reported in the study by Council et al. (15%). This simple fact explains most of the difference between the conclusions of the two studies. It must be noted, however, that the manner in which rear-end crashes were defined in the two studies differed and this may have contributed to the different percentages *(Garber et al., 2004, Council et al., 2005).* For this study, only those rear-end crashes attributable to the presence of the red phase were defined as rear-end crashes, whereas in the study by Council et al., all rear-end crashes were included, even if they were not attributable to the red light.

Further, other elements of the two studies are similar. The reduction in crashes attributable to red light running (25% to 34%) in this study was similar to the reduction in angle crashes reported by Council et al. at camera sites (25%). Even the limited data in

Table 7.1 are comparable to those noted by Council et al. The data in Table 7.1 suggest that angle crashes were moderately more severe than rear-end crashes. Council et al. *(Council et al., 2005)* similarly suggest that angle crashes have a moderately higher cost ($64,468) than rear-end crashes ($53,659)—a figure of about 20%.

The following question might then be asked: What would have been the results had this study taken advantage of the observation by Council et al. that suggests that angle crashes were slightly more costly than rear-end crashes by a figure of about 20%? Had this study weighted eliminated angle crashes by a factor of 1.2 relative to induced rear-end crashes, the resultant decrease in red light running crashes would still be smaller in magnitude than the large increase in rear-end crashes.

Finally, a more detailed examination of the Fairfax County data further suggests that the eliminated red light running injury crashes must be substantially more severe than the induced rear-end injury crashes to gain a net safety benefit from the cameras, as shown in Table 7.2. Table 7.2 shows that there were 8.7 fewer red light running injury crashes and 44.5 more rear-end injury crashes at the Fairfax County camera sites in the after period, which is attributable to presence of cameras. Thus for a net safety gain, the severity of an injury red light running crash should be more than 44.5/8.7 ~ 5.1 times the severity of a injury rear-end crash.

Table 7.2 Comparison of Actual Injury Crashes and “Would Have Been” Injury Crashes at Fairfax County Camera Intersections

	Actual Number of Crashes With Camera in After Period	Empirical Bayes Estimate (Crashes That Would Have Occurred Had There Been No Cameras) in After Period	Difference
Injury rear-end crashes*	94	49.5	44.5 (Increase)
Injury red light running crashes	23	31.7	8.7 (Decrease)
Other injury crashes	89	102.4	13.4(Decrease)
Total injury crashes	206	168.8	37.2 (Increase)

*Injury rear-end crashes refer to the subset of rear-end crashes defined previously where the count of injury is greater than 0.

3. *Does this study prove that cameras adversely impact safety?*

Certainly the most troubling aspect for red light proponents is the increase in total injury crashes, and until the impact of this increase is understood, it is difficult to use the Fairfax experience to state that cameras have a positive impact based on crash data alone. There are, however, three limitations of any empirical study, such as this, that must be stated. First, this study does not necessarily capture the full effect of drivers learning to change their behavior at the intersections: it may be the case that given more years of operation, an even greater number of drivers would have changed their behavior such that the rear-end crashes would not have increased quite so much. Second, this study focused on a single, albeit large, jurisdiction with urban and suburban roads with speed limits of 35 to 55 mph. It may be the case that roadways with different characteristics, or simply that crash histories of the other jurisdictions, could have yielded different results. Third, it may be possible that other confounding factors affected the results. Because of the emphasis on controlling for known factors such as volume and signal timing and the presence of α_y in the crash estimation model (Eq. 5.14) that attempts to control for unknown factors, this reason does not appear as likely as the other two.

(With any crash study, it is possible that crash types may not have been coded perfectly by law enforcement. For this particular study, however, the investigators do not believe such errors are problematic for two reasons. First, the crash narrative and diagram were studied rather than relying on a single classification code such as “angle.” Second, total injury crashes—all injury crashes within 150 feet of the intersection—increased as a result of camera enforcement according to the EB method.)

The statement of the three previous limitations is not a justification to discount the Fairfax County results: the increase in total injury crashes cannot be ignored. The limitations comprise an important context, however, with which to compare the findings of this work with those of future studies.

7.2. Usefulness of ANOVA and GLM Based Approach

ANOVA was used as an innovative tool to screen statistically significant second order interaction effects and GLM was used to model those effects with negative binomial distribution that is suitable for crash modeling as documented in the literature (Hadayaghi et al., 2003, Lord et al., 2005).

ANOVA proved to be useful for two reasons:

1) It illustrated the utility of using relatively homogenous group of sites and modeling geometric characteristics of a site by showing that there were a few factors which were not statistically significant in the first ANOVA analysis but were significant in second analysis when relatively homogenous set of sites were used and geometric characteristics such as number of through lanes, number of left turn lanes were modeled explicitly. For example, variable ITEDiff (yellow interval in excess of ITE recommended yellow interval) was statistically insignificant in the first ANOVA analysis and became

statistically significant in the second ANOVA analysis for total crashes, rear-end crashes and total injury crashes (see Table 6.4 and Table 6.5).

2) ANOVA served as a screening tool for interaction terms. Consider second ANOVA analysis where there were 8 main effects (such as Camera, ADT, CurbCuts etc.) There were twenty-eight second order terms possible (such as Camera*ADT etc.). ANOVA helped in narrowing down these terms total 28+8 = 36 terms to a manageable number of terms depending on the crash type, which were used in developing GLMs.

GLMs suggest that a quantitative analysis including significant interaction effects helps to identify the intersection location where cameras may have positive impact on safety. Most of the second order interaction terms were insignificant. However, interaction between camera presence and yellow interval difference (Existing yellow interval + Grace period (0.2 sec) – ITE recommended yellow interval) was significant for total crashes and rear-end crashes. The results showed that the cameras could have positive impact on safety where yellow interval is excessively higher than that recommended by ITE. Also, as in most of the cases in Fairfax County dataset yellow interval was set more than recommended by ITE, the finding doesn't imply that camera may not have beneficial effects at intersections with lower yellow intervals.

7.3. Sophistication in Analysis Vs Data Requirement

The results of the two crash statistical analyses main methods –EB, and GLM – are not in conflict. However, depending on the method used, the impacts of the camera on specific crash types may change from statistically significant to statistically insignificant, as was the case with total injury crashes. Total injury crashes were shown to have a significant increase from EB method and an insignificant increase from GLM method.

Also, the crash results obtained by the sophisticated statistical methods (the Empirical Bayes method and the GLM method) are consistent with the findings from the analysis performed using t-test with crash data being the same (Garber et al., 2004). The question that instantly may come to the mind of a researcher is about the degree of sophistication required in any analysis. In other words, when someone can get similar results from a lower level analysis, is it really required to do a more complicated analysis that has extensive data requirements and requires deep insight into the field of statistics to make inferences from the analysis?

Considering this case where consistent results obtained from different sophisticated levels of analyses reinforced the confidence in the results, however, the question if the cameras improve safety or not is still remains unanswered. To answer that a study examining detailed severity data was required. But because of the time shortage, injury severity data could not be collected in the given timeframe. In such a case it is recommended that researcher take a more pragmatic approach where he/she finds what more data shall be collected to answer the fundamental objective of the research and then collect that data for further analysis rather than doing more sophisticated level of analysis to get the same yet less useful results. A data analysis protocol as shown in the flowchart (Figure 7.1) may help prioritize the analytical approach.

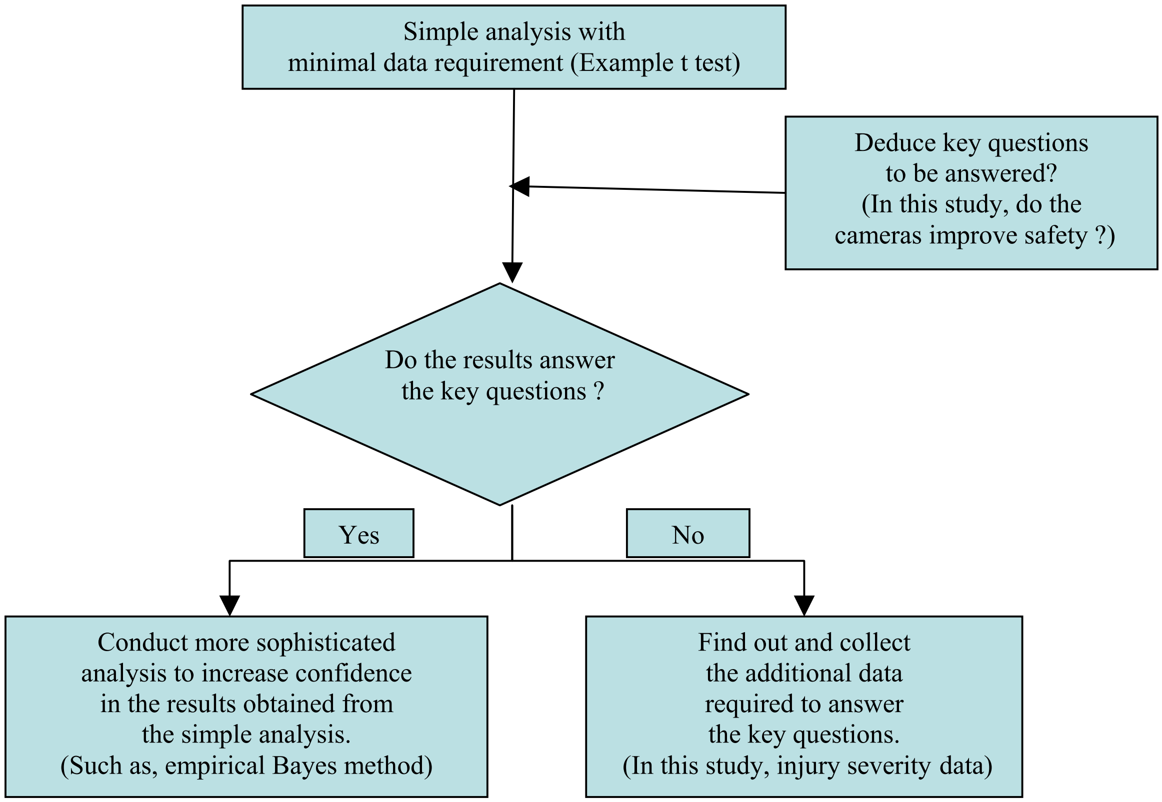

Figure 7.1 Data Analysis Protocol

Had it been possible to obtain severity data at the earlier stages of the research, it might not have been necessary to conduct more sophisticated level of analyses as the results obtained at the higher level of analyses would have been obtained at the lower level of analyses. Furthermore, in this particular study information obtained from the missing data would have been more important than the results obtained from the higher level of analyses.

8. CONCLUSIONS, RECOMMENDATIONS AND FUTURE WORK

8.1. Conclusions

- Photo-red enforcement definitely affects driver behavior. This is evidenced by decrease in citations, a statistically significant decrease in the number of crashes attributable to red light running and a statistically significant increase in the number of rear-end crashes. These findings are consistent with those in the majority of the literature surveyed.
- Photo red enforcement affect target crash types i.e. crashes attributable to red light running and rear-end crashes. The cameras are correlated with an increase in rear-end crashes and a decease in crashes attributable to red light running crashes.
- Red light cameras definitely affect intersection safety; whether this impact is positive or negative is not clear from the study. The cameras are associated with an increase in total injury crashes. A net safety gain may be realized if the injury severity of the eliminated red light running crashes is about 5 times greater than that of the induced rear-end crashes. However, because this study did not examine crash severity, a detailed study to examine the relative severity of crashes is required to determine if the cameras are having positive or negative impact on safety.
- ANOVA analysis illustrates the utility of selecting a relatively homogenous group of sites and explicitly modeling their distinct geometric characteristics.

- GLMs suggest the usefulness of including second order interaction effects in a quantitative analysis to identify the intersection location where cameras may have positive impact on safety.
- The camera may have safety benefit at the intersections where yellow interval is excessively higher than that recommended by ITE standards.
- Crash frequency increases as the yellow interval in excess of ITE recommended yellow interval increases.
- Geometric characteristics of an intersection such as the presence of frontage roads, and number of through lanes influence the crash experience.

8.2. Recommendations

- The study showed that the yellow interval and the intersection geometry (number of through lanes and number of left lanes) affect the crash frequency, which entails engineering judgment in terms of reviewing the yellow interval and the geometry of the intersection before installing photo-red enforcement system at the intersection.
- If photo-red enforcement system is to be implemented, it should be implemented at locations with higher ratio of red light running crashes to rear-end crashes as the study showed that cameras were correlated with a decrease in red light running (angle) crashes and an increase in rear-end crashes.
- For any research, more importance should be given to obtaining appropriate data of interest rather than focusing on sophistication in statistical analyses with a dataset, which may not produce conclusive results. As was the case with this study, which remained inconclusive, sophistication in statistical methods or details about confounding factors cannot be a substitute for data of interest – injury severity.

8.3. Future work

- A study that compares the severity of rear end crashes and angle crashes should be carried out to verify the impact of cameras on severity. Detailed injury data will be required for this type of study that would help in developing a more precise index of crash severity to compare the noted decrease in injury crashes attributable to red light running and the increase in total injury crashes. The study is already underway.
- The study suggested that yellow interval and camera had interacting impact on crashes. This area needs to be explored further. Researchers may be interested in identifying the time segments into red for violations, which are most dangerous or in other words are associated with relatively higher crash frequencies. Once those high-risk time segments into red are identified, yellow timings can be changed to reduce those time segments, which may result in higher level of safety. To identify high-risk time segments into red, one of the requirements would be to tie the red light running crashes with the associated violations.
- An analysis similar to what was performed in this study should be carried out with approach speed data replacing speed limits and volume data taking into account both major and minor road volumes.
- More data may be collected to explore the impact of speed variance, density and queue length etc. on intersection safety.
- Different forms of crash estimation models can be estimated and results can be compared across different models.

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APPENDIX A

Details of Literature Review

Tables A-1 and A-2 list the specific studies that comprised the literature review as well as the key findings. Table A-1 names the studies that are published independently as separate evaluations, and Table A-2 lists the studies that were used in the NCHRP Report by BMI.

Table A-1. Summary of Studies Used in the Literature Review

Author	Year	Location	Source	Name of the study	Summary
Andreassen, David	1995	Melbourne, Australia	Australian Road Research Board	A long term study of Red Light Cameras and Accidents	Contains statistical analysis of crash records for intersections in Melbourne, Australia. No long term reduction in crashes and there continues to be an increase in rear-end and adjacent approach collisions
BMI	2003	Fairfax County, Virginia		Study to Determine the Safety Effect of Red Light Running Camera Systems Installed at 10 Intersections in Fairfax County, Virginia	A very limited after period and a small sample size suggests a reanalysis of the data in future
Burkey., M., Obeng, K	2004	Greensboro, North Carolina	U.S. Department of Transportation, Research and Special Programs Administration, Washington	A Detailed Investigation of Crash Risk Reduction Resulting From Red Light Cameras in Small Urban Areas	Red light cameras did not reduce crashes nor severity; in fact, the report noted that red light cameras, increase crash rates by 40%.
Butler, Pamela Crenshaw	2001	Howard County	Howard University Thesis. Washington, DC:	A Quantifiable Measure of Effectiveness of Red Light Running Cameras at Treatment and Non-Treatment Sites	Contains statistical analysis of right-angle crash experience at two Howard County intersections. Found that reductions in crashes at the intersections were not statistically significant at the 95% confidence level, though they were close. No significant differences between the changes at the RLC and non-RLC intersections in Howard County, nor between the non-RLC sites in Howard County and several control sites in Pennsylvania.
Council, F.M., B. Persaud, K. Eccles, C. Lyon, and M.S. Griffith	Apr 2005		TFHRC	*Safety Evaluation of Red-Light Cameras,* BMI, April 2005.	The study showed that cameras provide modest to moderate economic benefit of between $39000 and $50000 per treated site year. The study also found out that cameras caused 24.6% decrease in angle crashes and 14.9% increase in

Author	Year	Location	Source	Name of the study	Summary
					rear end crashes.
Fox, H	1996	Glasgow, Scotland, UK	The Scottish Office, Central Research Unit.	Accidents at Signal Controlled Junctions in Glasgow.	Crash reductions at all signalized intersections in Glasgow considering 3-year period before and after automated enforcement. Report mentions other safety initiatives and intersection improvements underway, which may have influenced citywide decline in crashes.
Hillier, W., Ronczka, J.Schnerring,F.	1993	Sydney, Australia	Road Traffic Authority, NSW. Road Safety Bureau	An Evaluation of Red-Light Cameras in Sydney	50% reduction in angle and right-turn opposing collisions, 20-60% increase in rear-end collisions
Lum, KM; Wong, YD	2003	Singapore	Journal of Transportation Engineering	Impact of Red Light Camera on Violation Characteristics	Red running violations were substantially reduced by more than 40% at camera approaches. Overall, there was aggregated net reduction of about 7% across all approaches.
	2002		Journal of Safety Research	A Study of Stopping Propensity at matured Red Light Camera Intersections	The propensity to stop at camera approaches was found to be about 17 times more frequent than at non-camera approaches.
	2002		Road and transport research	Effects of Red Light Camera Installation on Driver Behavior at a Signalized Cross-Junction in Singapore	The revealed stopping/crossing decisions of non-platoon vehicle drivers were modeled as they responded to the onset of the yellow signal, along with a number of traffic and behavioral variables.
	1997		Road and Transport Research, Vol. 6, No. 2, 1997, pp. 72–80.	The Impact of Red-Light Surveillance Cameras on Road Safety in Singapore	Right angle collisions and total collisions were reduced by 8 % and 7% respectively with slight increase of 5% in rear-end collisions.
Mann, T., S. Brown, and C. Coxon	1994	Adelaide, Australia	South Australia Department of Transport, Adelaide, South Australia	Evaluation of the Effects of Installing Red Light Cameras at Selected Adelaide Intersections	The sites with Red Light Cameras and other modifications showed significantly greater crash reductions than the control group, but the effect of RLR cameras couldn't be isolated.
	1997	London	London Research Center, Environment and Transport Studies	An Analysis of Accident and Casualty Data 36 Months “After” Implementation and Comparison with the 36 Months “Before” Data,	A 16% reduction in "disobeyed traffic signal" crashes was observed, but it was not statistically significant.

Author	Year	Location	Source	Name of the study	Summary
Mullen, D	2001	City of Edmonton,Alberta, Canada		The City of Edmonton Red Light Camera Program in Review	Average violation frequency decreased from 9 violations per day to 2.5 violations per day after the implementation of the automated enforcement with 6 cameras operating at 12 locations. Overall figures indicate the success of the program in reducing red light violations.
McGee, HW; Eccles, KA	2003		TRB, NCHRP	Impact of Red Light Camera Enforcement on Crash Experience (NCHRP synthesis)	Based on the information available through published literature, various websites, and a survey, the report concludes that red light running automated enforcement can be an effective safety countermeasure. However, there is currently insufficient empirical evidence based on statistically rigorous experimental design to state this conclusively.
	2002			Safety Impact of Red Light Camera Enforcement Program	A critical review of the literature dealing with the impacts of red light cameras on crashes
Per Garder	2004	Maine (Cameras not present here)	Department of Civil and Environmental Engineering, University of Maine, Orono, Maine	Traffic Signal Safety: Analysis of Red Light Running in Maine	More enforcement by police or automatic surveillance is by the public considered the most effective ways to reduce red-light running. Finally, the most important factor in reducing red-light running frequency, as well as the number of serious crashes caused by red-light running, is never having a posted speed limit greater than 35 mph through a signalized intersection.
Retting, RA; Ferguson, SA; Hakkert, AS	2002			Effect of Red Light Cameras on Violations and Crashes: A review of International Literature	The studies indicate that, overall, injury crashes, including rear-end collisions, were reduced by 25-30% as a result of camera enforcement.
	2002		IIHS	An Evaluation of the Effectiveness of Red-Light Cameras at Signalized Intersections	This paper brings together literature that has been published on the subject of red-light-running (RLR) crashes.
Retting, Richard A.; Kyrychenko, Sergey Y	2002	Oxnard, California	American Journal of Public Health	Reduction in Injury Crashes Associated with Red Light Camera Enforcement in Oxnard, California	Overall, crashes at signalized intersections throughout Oxnard were reduced by 7% and injury crashes were reduced by 29%. The right-angle crashes were reduced by 32%, and right-angle crashes involving injuries were reduced by 68%.
	2001		IIHS	Crash Reductions Associated with Red Light Camera Enforcement in Oxnard, California	
Retting, Richard A.	2000		ITE Annual Meeting	Reducing Red Light Running Crashes: A Research Perspective	Red light cameras can produce a strong deterrent effect and drivers in urban communities generally support this type of camera enforcement.

Author	Year	Location	Source	Name of the study	Summary
Retting, RA; Williams, AF; Farmer, CM; Feldman, AF	1999	Fairfax City, Virginia	ITE Journal	Evaluation of Red Light Camera Enforcement in Fairfax, VA, USA	Overall reductions in violations at the five camera sites were 7% after 3 months and 44% after one year. Overall reductions at the two non-camera sites were 14% after 3 months and 34% after one year. The overall violation rate at the control sites essentially was unchanged. Public support for camera use increased from 75% before enforcement to 84% one year after enforcement.
Ruby, D.E., Hobeika A	2003	Fairfax County, Virginia	Transportation Research Board, 82nd annual meeting	Assessment of Red Light Running Cameras in Fairfax County , Virginia	Violation rates reduced by 36% over the initial three months and by 69% after six months of enforcement. The accident data also showed a reduction of 40% in accidents.
Status Report	2001	Oxnard, California	IIHS	Red Light Cameras Yield Big Reductions in Crashes and Injuries	Installation of red light cameras on only a fraction of the city's intersections reduces serious crashes and injuries at intersections across the city. The article also details a survey showing strong public support for cameras' use and recommends legislative changes to make it easier for localities to install them.
	2002	California	California State Auditor/Bureau of State Audits	Red Light Camera Programs: *Although They Have Contributed to a Reduction in Accidents, Operational Weaknesses Exist at the Local level*	
		San Diego	PB FARRADYNE	San Diego Photo Enforcement System Review http://www.sandiego.gov/police/pdf/photochap2.pdf	After six months 20 to 24 % reduction in violations that remained same for longer period of camera operation, significant reductions in the accidents attributable to red light running, accident rate is highest where through approach is monitored. Overall accident rate increased by 3 % after cameras installation due to increase in rear-end accidents.
A Report to Parliament	1993	Perth, Australia	Office of Auditor General	Improving Road Safety: Speed and Red Light Cameras and The Road Trauma Trust Fund, Perth Australia	40% reduction in angle collisions and no increase in rear-end collisions
United States. Congress. House. Office of the Majority Leader	2001			The Red Light Running Crisis: Is It Intentional ?	The document concludes: "The only documented benefit to red light cameras is to the pocketbook of local governments who use the devices to collect millions in revenue. We traded away our privacy for this. We gave up our constitutional protections for this. In return, we are less safe. That is the red light camera scam, and it has gone on for far too long"

Table A-2: Findings of Crash Evaluations As Reported By Jurisdictions On a Survey Conducted By NCHRP

Location	Type of Evaluation	Findings
Baltimore County, MD	1-yr B/A	Total crashes decreased 51%; intersection related decreased 55%; RLR crashes decreased 30%; injury crashes decreased 51%; PDO crashes decreased 51%
Boulder, CO	32-month after evaluation	57% reduction in red light-related accidents
Charlotte, NC	B/A for 3 yr for 17 intersections	Overall angle crashes reduced by 37% at intersections with cameras and 60% for approaches with cameras; all crash types reduced by 19%; crash severity reduced by 16%; rear-end crashes increased by 4% on camera approaches
Garden Grove, CA	1-yr B/A compared to 5 other high violation locations	56.2% reduction in right-of-way violation accidents; 1.2% increase in rear-end accidents
Howard County, MD (two separate evaluations)	1-yr B/A for 24 intersections	Rear-end collisions increased by 6%; angle collisions decreased by 47%; other collisions decreased by 11% Reductions in total collisions from 1998 to 2000
	1+-yr B/A for 25 intersections	For all RLR intersections: 30% decrease for rear-end; 42% decrease for angle; 21% decrease for other; 31% decrease total
Laurel, MD		Reduction in number of accidents at all locations
Los Angeles County,CA		Accident rates for 3 of 5 locations reduced, 4th remained relatively the same, and 5th did not improve
Mesa, AZ	Yearly collision rates	Intersection-related accident rates (per population) have decreased each of 5 years since installation
Montgomery County, MD	B/A for 2 yr	Overall number of crashes went down slightly, but probably not significant
Paradise Valley, AZ	B/A; time frame unknown	Same number of collisions, but reduced severity
Sacramento, CA	Comparison of crashes 1 yr B/A	Reductions: 10% for all crashes; 27% for injury crashes; 26% for angle crashes; 12% for rear-end crashes; 39% for red light crashes
San Diego, CA	B/A for 2 yr at 16 intersections	Injury accidents remained the same at most locations; but incidents of RLR decreased dramatically
San Francisco City, CA	5-yr B/A for 1st camera in '96	RLR collisions declined

Location	Type of Evaluation	Findings
Scottsdale, AZ	Comparison of RLR accidents city-wide B/A	RLR accidents dropped first year after cameras but have crept up but not to the level before installation. RLR accidents at camera locations are too low to make a conclusion. Difficult to isolate RLR camera effect. Summary data provided
Tempe, AZ	4-yr B/A	Collision rate for both intersections has shown increases and decreases since inception
Notes: B/A = Before and After; RLR = Red light running; PDO = Property damage only.		

APPENDIX B

Two-Part Survey Sent to Virginia Jurisdictions

Survey of Photo-Red Enforcement Programs in Virginia

Conducted by: Virginia Transportation Research Council
Please return to: (434) 293-1990 (fax) or Wayne.Ferguson@Virginiadot.org

Name of the Contact: Commander Daniel Gollhardt　　Locality: City of Alexandria
Email: Daniel.Gollhardt@ci.alexandria.va.us
Fax: (703) 838-6309　also B CATON W HANES P STORY

1. Please provide the date when Alexandria's enforcement program was initiated. 11/97

2. Pleases indicate the specific objectives of your program (check all that apply).

☒ To reduce violations
☒ To reduce accidents
☒ To increase pedestrian safety
☒ To change driver behavior
☐ Other, please specify

3. Please indicate below who is responsible for the different functions shown (check all that apply).

	Project Planning and Management	Equipment Ownership	Design and Installation	Operation and Maintenance	Citation Data Processing	Decision To Issue Citation	Violator Inquiries	Archive Violation Data	Public Information Program
Alexandria Police Department	☒	☐	☒	☒	☒	☒	☒	☒	☒
Alexandria Traffic Engineering Section	☒	☐	☒	☒	☐	☐	☐	☐	☐
VDOT Northern Virginia District	☐	☐	☐	☐	☐	☐	☐	☐	☐
Contractor	☐	☒	☒	☒	☒		☒	☒	☐
Other, specify	City MANAGER STAFF ☒ & COUNCIL	☐	☐	☐	☐	☐	☐	☐	☐

4. Please indicate the criteria used to select intersections for camera locations (check all that apply).

☒ Accident data　☒ Violation data　☒ Input from police personnel
☒ Input from citizens　☒ Site review by　(Specify agency)
☒ Other, please specify TRAFFIC VOLUME

5. What is the number of cameras currently used in your locality? 3

6. Are these cameras:

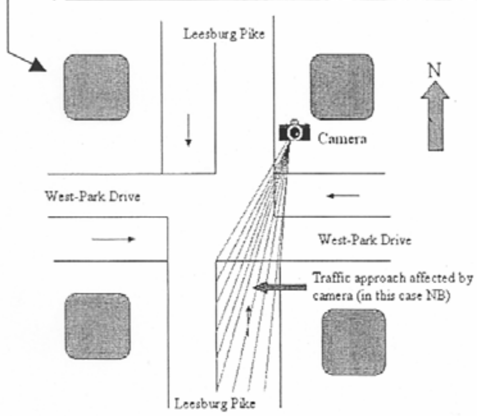
☐ Stationary　☒ Rotated among different intersections

7. If cameras are rotated, what is the number of camera housings in your locality?

8. In the table below, please name the intersections where cameras are located.

Intersection Locations

Intersections Where Cameras Are in Use		
Location: Street 1/ Street2	Traffic approach affected by camera NB/SB/EB/WB	Date camera was installed
Example. Leesburg Pike/ Westpark Drive	*NB*	*15th Oct, 2000*
PATRICK & GIBBON STS.	SB	11/97
SEMINARY RD & NOTTINGHAM DR.	NWB	11/97
DUKE & WALKER STS.	EB	11/97
DUKE STREET & TAYLOR RUN PARKWAY	WB	3/04



9. How long after the light turns red does the camera begin taking pictures (lag time)?

☐0.1 sec ☐0.2 sec ☒0.3 sec ☐0.4 sec ☐ Other, please specify

10. Please give the name of the manufacturer of the cameras.

11. Please indicate the camera technology.

☒35 mm wet film ☐Digital still photos ☐Digital video ☐ Other, please specify

12. Does the agency use a contractor to operate the red light camera system?

☒ Yes (If yes, please skip question 13 and go to question 14)
☐ No (If no, please go to question 13 and skip question 14)

13. **Agency-operated systems:** Please provide us with the following cost data for your program.

Initial Purchase Cost	$
Installation Cost	$
Annual Maintenance Cost	$
Annual Revenues from Violations Issued	$
Any other financial data you deem relevant	

14. **Contractor-operated systems**: Please answer questions (a) and (b).

a. Please complete the following table. (Check all that apply)

Payment Option	Equipment Purchase Price		Equipment Installation Price		Equipment Maintenance Price		Citation Data Processing Price	
Fixed Price Payment	☐	$	☒ *	$27,000/ INTERSECTION	☐	$	☐	$
Fixed Monthly Payments	☐	$	☐	$	☒	$	☒	$27,750
Time Worked and Materials Used	☐	$	☐	$	☐	$	☐	$
Is there any threshold (maximum/minimum) limit on the payments made to the contractor? If yes, briefly explain								

* THE $27K cost is only for intersections installed after 11/97.

b. How does the contractor get paid? (Check all that apply)

☐Per violation ☐ Per citation ☒Flat fee ☐ Other, please specify

Photo Red Light Questionnaire
15. Impact Data

a. Red light violations at sites where cameras are used versus comparable site where cameras are not used.

Response: No. We do not have violation data by location for non-camera sites.

b. Crash data at sites where cameras are used versus comparable site where cameras are not used.

Response: We can access crash data since 2001 for camera sites. See attached table. We are unable to identify comparable non-camera sites.

c. Traffic volume data for camera sites and comparable non-camera sites.

Response: We are still checking on traffic volume data for camera sites.

d. Signal timing data for camera sites and comparable non-camera sites.

Response: Our signal timing is based on intersection design and speed limits, not the presence of Photo Red light (i.e., red light camera intersections are no different than other intersections).

e. Speed data for camera sites and comparable non-camera sites.

Response: We capture speed at the time of violation in the intersection at Photo Red sites only. Comparison not possible. Photo sites are operated in 25 and 35 MPH zones.

f. Comparison of costs and benefits when comparing tradition enforcement to photo-red enforcement. Does one technique have a higher rate of successful appeals.

Response: We have not done formal cost analysis. It is obvious that photo enforcement is more effective than traditional (officer operated) in most respects. Photo enforcement is 24/7, traditional is not. No agency has the personnel to stake a red light for several hours a day let alone 24/7. Another important aspect is the fact that photo enforcement can be conducted safely without the need to pursue and stop violators in traffic lanes. In fact, some locations are virtually unenforceable from a safety standpoint due to design and volume of traffic. In these locations, enforcement is likely to be more dangerous than the red light violation.

Photo enforcement has fewer successful appeals. Photos and system data on the violation provide clear and convincing evidence in court as opposed to the "judgement" issues raised in court relative to officer issued citations. In addition, the $50 civil penalty assessed for a photo violation is not appealable to Circuit Court.

g. Any surveys or polls indicating public opinion of photo-red enforcement?

Response: No official surveys conducted. However, informally, requests for new photo red sites far outweigh complaints about photo enforcement.

Commander Daniel Gollhardt
Alexandria Police Department
FAX: (703) 838-6309
Email: Daniel.Gollhardt@ci.alexandria.va.us

Dear Commander Gollhardt,

Earlier in July we sent you a questionnaire regarding Alexandria's photo-red enforcement programs, which we are required to study as part of a report requested by Virginia Transportation Secretary Whitt Clement. The purpose of this letter is to obtain the additional crash and violation data we discussed on the last page of the questionnaire. To minimize your effort, we will accept your data in their native format. We ask that you ensure, however, that we can extract the following information if either you have these data or another person in Alexandria has these data:

(1) For each of the three Alexandria intersections where there is a red light camera:

a.	*List of red light violations* by date and hour
b.	List of crashes. For each crash, please include date, time, severity, type (angle, rear-end), approach (NB, SB, EB, or WB), and violation that indicates whether or not crash was related to red light running
c.	Individual approach volumes
	Percentage of truck volumes
d.	Cycle length
	Yellow interval
	Phasing
e.	Posted speed limit
	Mean approach speed
	85th percentile approach speed
f.	*Dates of any changes* for the above such as changes in yellow intervals.

(2) The same data as above for at least three comparable intersections where there is not a red light camera

(3) Any other person who might be able to provide information on the following:

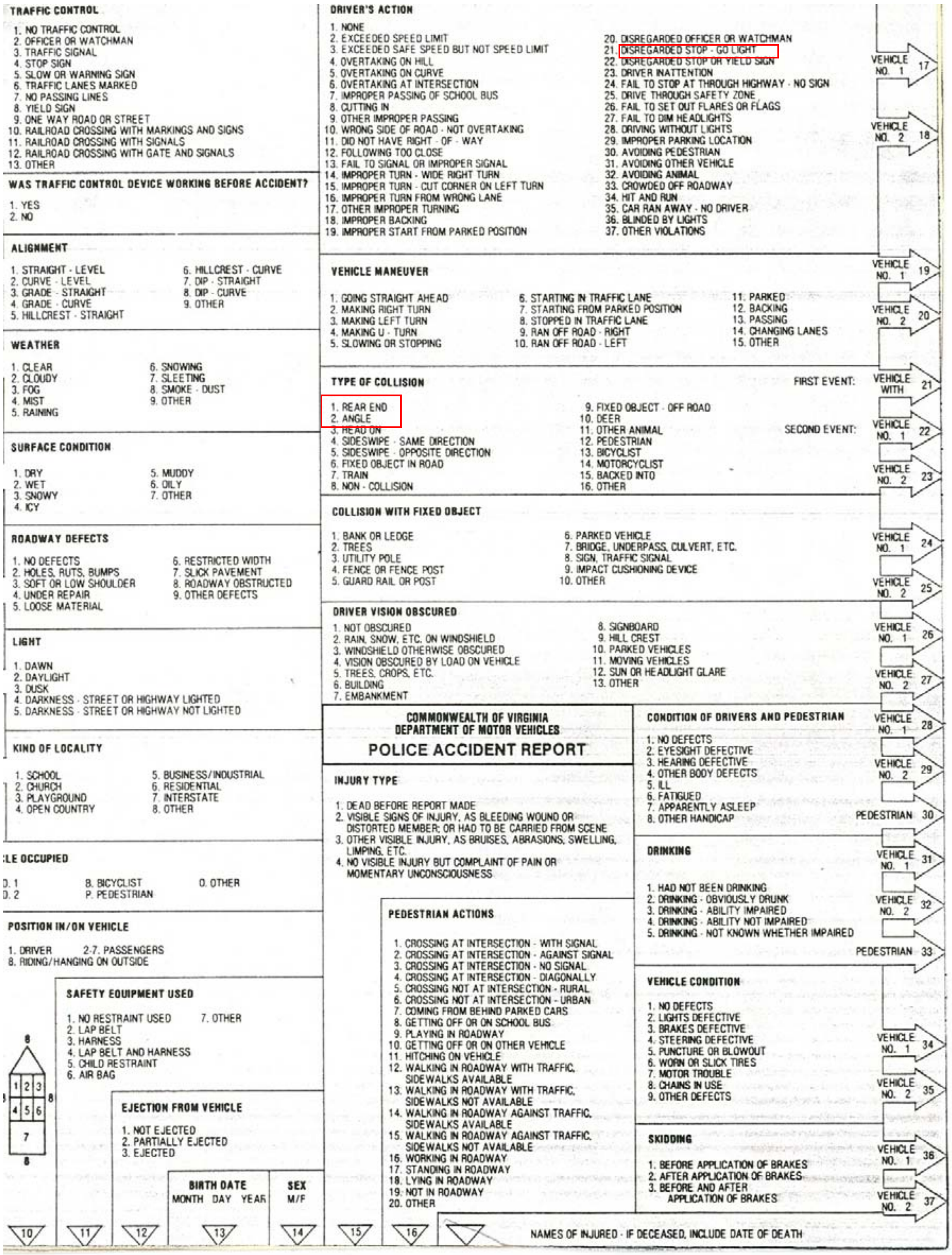
- Comparison of costs and benefits when comparing traditional enforcement to photo-red enforcement. (For example, does one technique have a higher rate of successful appeals?)
- Any surveys or polls indicating public opinion of photo-red enforcement.

(4) We need detailed violation data for the cameras such as the exact fraction of a second a violation occurred after the signal turned red. Who should we contact for that information?

For example, the contact might be (a) your agency, (b) the traffic engineering department, or (c) the contractor (ACS).

Thank you for your assistance,
Wayne S. Ferguson, Associate Director; Virginia Transportation Research Council; 530 Edgemont Road; Charlottesville, Virginia 22903; (434) 293-1900 (voice); (434) 293-1990 (fax)

APPENDIX C



TRAFFIC CONTROL

1. NO TRAFFIC CONTROL
2. OFFICER OR WATCHMAN
3. TRAFFIC SIGNAL
4. STOP SIGN
5. SLOW OR WARNING SIGN
6. TRAFFIC LANES MARKED
7. NO PASSING LINES
8. YIELD SIGN
9. ONE WAY ROAD OR STREET
10. RAILROAD CROSSING WITH MARKINGS AND SIGNS
11. RAILROAD CROSSING WITH SIGNALS
12. RAILROAD CROSSING WITH GATE AND SIGNALS
13. OTHER

WAS TRAFFIC CONTROL DEVICE WORKING BEFORE ACCIDENT?

1. YES
2. NO

ALIGNMENT

1. STRAIGHT - LEVEL
2. CURVE - LEVEL
3. GRADE - STRAIGHT
4. GRADE - CURVE
5. HILLCREST - STRAIGHT
6. HILLCREST - CURVE
7. DIP - STRAIGHT
8. DIP - CURVE
9. OTHER

WEATHER

1. CLEAR
2. CLOUDY
3. FOG
4. MIST
5. RAINING
6. SNOWING
7. SLEETING
8. SMOKE - DUST
9. OTHER

SURFACE CONDITION

1. DRY
2. WET
3. SNOWY
4. ICY
5. MUDDY
6. OILY
7. OTHER

ROADWAY DEFECTS

1. NO DEFECTS
2. HOLES, RUTS, BUMPS
3. SOFT OR LOW SHOULDER
4. UNDER REPAIR
5. LOOSE MATERIAL
6. RESTRICTED WIDTH
7. SLICK PAVEMENT
8. ROADWAY OBSTRUCTED
9. OTHER DEFECTS

LIGHT

1. DAWN
2. DAYLIGHT
3. DUSK
4. DARKNESS - STREET OR HIGHWAY LIGHTED
5. DARKNESS - STREET OR HIGHWAY NOT LIGHTED

KIND OF LOCALITY

1. SCHOOL
2. CHURCH
3. PLAYGROUND
4. OPEN COUNTRY
5. BUSINESS/INDUSTRIAL
6. RESIDENTIAL
7. INTERSTATE
8. OTHER

LE OCCUPIED

).1).2 8. BICYCLIST P. PEDESTRIAN O. OTHER

POSITION IN/ON VEHICLE

1. DRIVER 2-7. PASSENGERS
8. RIDING/HANGING ON OUTSIDE

SAFETY EQUIPMENT USED

1. NO RESTRAINT USED
2. LAP BELT
3. HARNESS
4. LAP BELT AND HARNESS
5. CHILD RESTRAINT
6. AIR BAG
7. OTHER

EJECTION FROM VEHICLE

1. NOT EJECTED
2. PARTIALLY EJECTED
3. EJECTED

BIRTH DATE MONTH DAY YEAR — SEX M/F

DRIVER'S ACTION

1. NONE
2. EXCEEDED SPEED LIMIT
3. EXCEEDED SAFE SPEED BUT NOT SPEED LIMIT
4. OVERTAKING ON HILL
5. OVERTAKING ON CURVE
6. OVERTAKING AT INTERSECTION
7. IMPROPER PASSING OF SCHOOL BUS
8. CUTTING IN
9. OTHER IMPROPER PASSING
10. WRONG SIDE OF ROAD - NOT OVERTAKING
11. DID NOT HAVE RIGHT - OF - WAY
12. FOLLOWING TOO CLOSE
13. FAIL TO SIGNAL OR IMPROPER SIGNAL
14. IMPROPER TURN - WIDE RIGHT TURN
15. IMPROPER TURN - CUT CORNER ON LEFT TURN
16. IMPROPER TURN FROM WRONG LANE
17. OTHER IMPROPER TURNING
18. IMPROPER BACKING
19. IMPROPER START FROM PARKED POSITION
20. DISREGARDED OFFICER OR WATCHMAN
21. DISREGARDED STOP - GO LIGHT
22. DISREGARDED STOP OR YIELD SIGN
23. DRIVER INATTENTION
24. FAIL TO STOP AT THROUGH HIGHWAY - NO SIGN
25. DRIVE THROUGH SAFETY ZONE
26. FAIL TO SET OUT FLARES OR FLAGS
27. FAIL TO DIM HEADLIGHTS
28. DRIVING WITHOUT LIGHTS
29. IMPROPER PARKING LOCATION
30. AVOIDING PEDESTRIAN
31. AVOIDING OTHER VEHICLE
32. AVOIDING ANIMAL
33. CROWDED OFF ROADWAY
34. HIT AND RUN
35. CAR RAN AWAY - NO DRIVER
36. BLINDED BY LIGHTS
37. OTHER VIOLATIONS

VEHICLE NO. 1 17 — VEHICLE NO. 2 18

VEHICLE MANEUVER

1. GOING STRAIGHT AHEAD
2. MAKING RIGHT TURN
3. MAKING LEFT TURN
4. MAKING U - TURN
5. SLOWING OR STOPPING
6. STARTING IN TRAFFIC LANE
7. STARTING FROM PARKED POSITION
8. STOPPED IN TRAFFIC LANE
9. RAN OFF ROAD - RIGHT
10. RAN OFF ROAD - LEFT
11. PARKED
12. BACKING
13. PASSING
14. CHANGING LANES
15. OTHER

VEHICLE NO. 1 19 — VEHICLE NO. 2 20

TYPE OF COLLISION

1. REAR END
2. ANGLE
3. HEAD ON
4. SIDESWIPE - SAME DIRECTION
5. SIDESWIPE - OPPOSITE DIRECTION
6. FIXED OBJECT IN ROAD
7. TRAIN
8. NON - COLLISION
9. FIXED OBJECT - OFF ROAD
10. DEER
11. OTHER ANIMAL
12. PEDESTRIAN
13. BICYCLIST
14. MOTORCYCLIST
15. BACKED INTO
16. OTHER

FIRST EVENT: VEHICLE WITH 21 — SECOND EVENT: VEHICLE NO. 1 22 — VEHICLE NO. 2 23

COLLISION WITH FIXED OBJECT

1. BANK OR LEDGE
2. TREES
3. UTILITY POLE
4. FENCE OR FENCE POST
5. GUARD RAIL OR POST
6. PARKED VEHICLE
7. BRIDGE, UNDERPASS, CULVERT, ETC.
8. SIGN, TRAFFIC SIGNAL
9. IMPACT CUSHIONING DEVICE
10. OTHER

VEHICLE NO. 1 24 — VEHICLE NO. 2 25

DRIVER VISION OBSCURED

1. NOT OBSCURED
2. RAIN, SNOW, ETC. ON WINDSHIELD
3. WINDSHIELD OTHERWISE OBSCURED
4. VISION OBSCURED BY LOAD ON VEHICLE
5. TREES, CROPS, ETC.
6. BUILDING
7. EMBANKMENT
8. SIGNBOARD
9. HILL CREST
10. PARKED VEHICLES
11. MOVING VEHICLES
12. SUN OR HEADLIGHT GLARE
13. OTHER

VEHICLE NO. 1 26 — VEHICLE NO. 2 27

COMMONWEALTH OF VIRGINIA
DEPARTMENT OF MOTOR VEHICLES
POLICE ACCIDENT REPORT

INJURY TYPE

1. DEAD BEFORE REPORT MADE
2. VISIBLE SIGNS OF INJURY, AS BLEEDING WOUND OR DISTORTED MEMBER; OR HAD TO BE CARRIED FROM SCENE
3. OTHER VISIBLE INJURY, AS BRUISES, ABRASIONS, SWELLING, LIMPING, ETC.
4. NO VISIBLE INJURY BUT COMPLAINT OF PAIN OR MOMENTARY UNCONSCIOUSNESS

PEDESTRIAN ACTIONS

1. CROSSING AT INTERSECTION - WITH SIGNAL
2. CROSSING AT INTERSECTION - AGAINST SIGNAL
3. CROSSING AT INTERSECTION - NO SIGNAL
4. CROSSING AT INTERSECTION - DIAGONALLY
5. CROSSING NOT AT INTERSECTION - RURAL
6. CROSSING NOT AT INTERSECTION - URBAN
7. COMING FROM BEHIND PARKED CARS
8. GETTING OFF OR ON SCHOOL BUS
9. PLAYING IN ROADWAY
10. GETTING OFF OR ON OTHER VEHICLE
11. HITCHING ON VEHICLE
12. WALKING IN ROADWAY WITH TRAFFIC, SIDEWALKS AVAILABLE
13. WALKING IN ROADWAY WITH TRAFFIC, SIDEWALKS NOT AVAILABLE
14. WALKING IN ROADWAY AGAINST TRAFFIC, SIDEWALKS AVAILABLE
15. WALKING IN ROADWAY AGAINST TRAFFIC, SIDEWALKS NOT AVAILABLE
16. WORKING IN ROADWAY
17. STANDING IN ROADWAY
18. LYING IN ROADWAY
19. NOT IN ROADWAY
20. OTHER

CONDITION OF DRIVERS AND PEDESTRIAN

1. NO DEFECTS
2. EYESIGHT DEFECTIVE
3. HEARING DEFECTIVE
4. OTHER BODY DEFECTS
5. ILL
6. FATIGUED
7. APPARENTLY ASLEEP
8. OTHER HANDICAP

VEHICLE NO. 1 28 — VEHICLE NO. 2 29 — PEDESTRIAN 30

DRINKING

1. HAD NOT BEEN DRINKING
2. DRINKING - OBVIOUSLY DRUNK
3. DRINKING - ABILITY IMPAIRED
4. DRINKING - ABILITY NOT IMPAIRED
5. DRINKING - NOT KNOWN WHETHER IMPAIRED

VEHICLE NO. 1 31 — VEHICLE NO. 2 32 — PEDESTRIAN 33

VEHICLE CONDITION

1. NO DEFECTS
2. LIGHTS DEFECTIVE
3. BRAKES DEFECTIVE
4. STEERING DEFECTIVE
5. PUNCTURE OR BLOWOUT
6. WORN OR SLICK TIRES
7. MOTOR TROUBLE
8. CHAINS IN USE
9. OTHER DEFECTS

VEHICLE NO. 1 34 — VEHICLE NO. 2 35

SKIDDING

1. BEFORE APPLICATION OF BRAKES
2. AFTER APPLICATION OF BRAKES
3. BEFORE AND AFTER APPLICATION OF BRAKES

VEHICLE NO. 1 36 — VEHICLE NO. 2 37

10 11 12 13 14 15 16

NAMES OF INJURED - IF DECEASED, INCLUDE DATE OF DEATH

Figure D1. Excerpt of FR300 Crash Report Form Template (Rev. 9/84)
(Annotation added by the author)

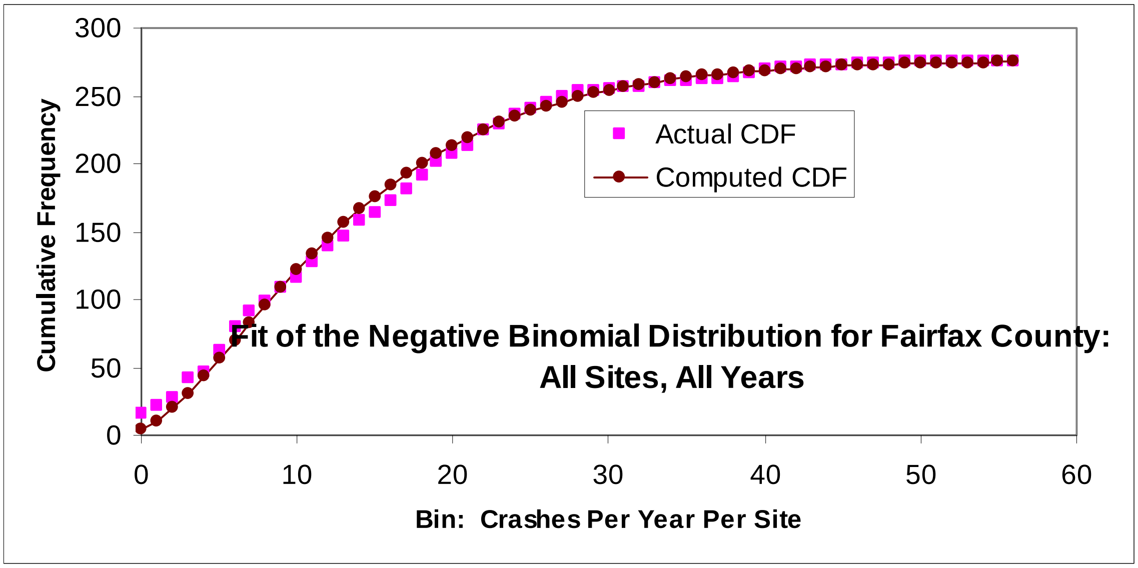
APPENDIX D

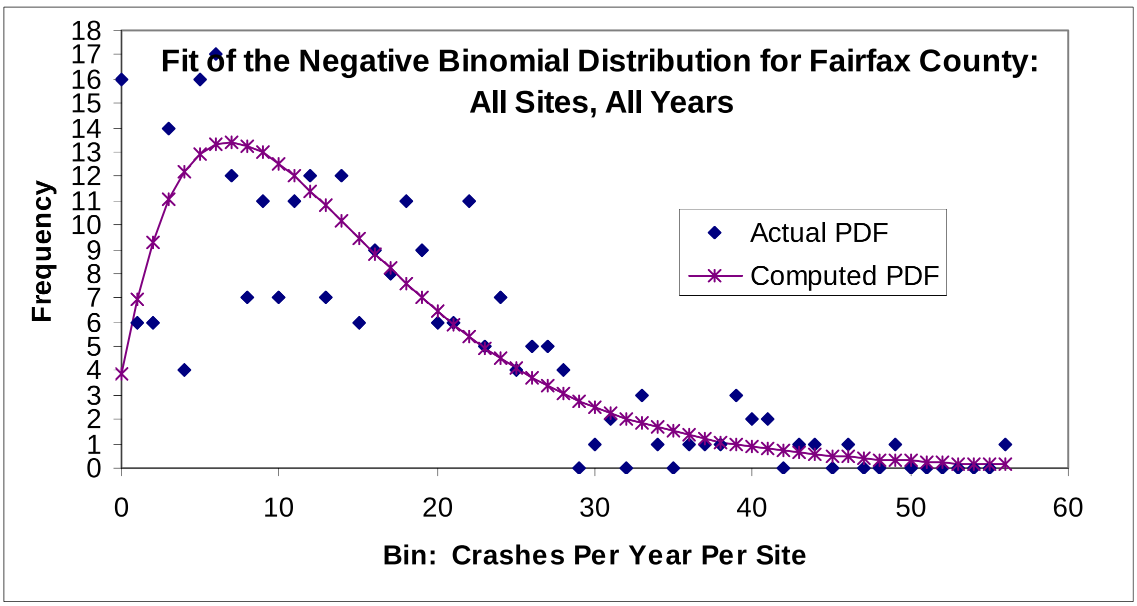
Comparison Sites in Fairfax County

Intersection	Signal #	County
Lee Hwy & Nutley	29045	Fairfax
Lee Hwy & Circle Woods	29055	Fairfax
Dolley Madison Blvd & Old Chain Bridge Rd	123025	Fairfax
Dolley Madison Blvd & Old Dominion	123035	Fairfax
Chain Bridge & Old Courthouse	123075	Fairfax
Chain Bridge & Jermantown	123105	Fairfax
Lawyers & West Ox/Folkstone	602005	Fairfax
Old Keene Mill & Hanover Ave.	644040	Fairfax
Old Keene Mill & Greeley Blvd	644050	Fairfax
Old Keene Mill & Huntsman	644070	Fairfax
Sully Rd. & Willard	28071	Fairfax
Sully & Westfields Blvd	28075	Fairfax
Sully Rd. & Braddock Rd/Walney	28080	Fairfax
Nutley & Swawnee/Metro So.	243010	Fairfax
Nutley & Hermosa Dr.	243015	Fairfax
Reston Pkwy & Sunset Hills	602045	Fairfax
Reston Pkwy & Bluemont	602046	Fairfax
Reston Pkwy & Temporary Rd/ New Dominion	602047	Fairfax
Reston Pkwy & Bowmantown/Bowmangreen	602050	Fairfax
West Ox & Monument Dr.	608020	Fairfax
West Ox & Cedar Lakes/4901 Hanger	608023	Fairfax
West Ox & Fair Lakes Pkw	608025	Fairfax
West Ox & Price Club Connector Rd.	608030	Fairfax
West Ox & Piney Branch Rd/Transfer	608031	Fairfax
Van Dorn & Oakwood	613031	Fairfax
Van Dorn & Crown Royal	613035	Fairfax
Van Dorn & Woodfield/Chrysanthemum	613040	Fairfax
Van Dorn & Franconia	613045	Fairfax
Braddock & Port Royal	620020	Fairfax
Braddock & Queensbury	620025	Fairfax
Braddock & Wakefield Chapel	620030	Fairfax
Braddock & Southhampton	620035	Fairfax
Braddock & Kings Park	620040	Fairfax

APPENDIX E

Fit of Negative Binomial Distribution for Fairfax County Crash Data





APPENDIX F

Introduction to Generalized Linear Models

The class of generalized linear models is essentially an extension of traditional linear models and consists of following three components:

1. Response Probability Distribution

The response variables (y_i) are assumed to be independent and to have a probability distribution from an exponential family. The family of the exponential distributions includes Poisson distribution, Binomial distribution, Negative Binomial distribution, Gamma distribution etc. (Example: crash count per unit time with Negative Binomial or Poisson probability distribution.)

2. Linear Component

The linear component (η_i) is defined as it is defined for the traditional linear models.

$$\eta_i = \sum_{j=1}^{k} b_j X_{ij} \qquad \text{(Eq. F-1)}$$

Where, X_{ij} = Explanatory variables

And b_j's are model parameters.

3.Link Function

The link function describes how the expected value μ_i of the response variable y_i is related to the linear predictor (η_i) defined in Eq. F-1.

$$f(\mu_i) = \sum_{j=1}^{k} b_j X_{ij} \qquad \text{(Eq. F-2)}$$

Thus, in essence, a GLM allows the mean of a population depends on a linear predictor through a nonlinear link function.

Mathematical Form

Table F1 compares the Poisson and Negative Binomial distribution based GLMs with traditional linear model. Traditional linear model is also included in the Table F1 to emphasize that it is also a specific case of generalized linear model when link function is an identity function and response probability distribution is a continuous normal distribution.

Table F1: Comparison of GLM based Models with Traditional Linear Model

	Traditional Linear Model	Poisson Distribution Based GLM	Negative Binomial Distribution Based GLM
Response Variable	Continuous	Count	Count
Response Probability Distribution[1]	Normal	Poisson	Negative Binomial
Linear Predictor	$\eta_i = \sum_{j=1}^{k} b_j X_{ij}$	$\eta_i = \sum_{j=1}^{k} b_j X_{ij}$	$\eta_i = \sum_{j=1}^{k} b_j X_{ij}$
Link Function	$\eta_i = \mu_i$	$\eta_i = \mu_i$	$\eta_i = \log(\mu_i)$

Note 1: The response probability distributions are given below.

Normal Distribution:

$$f(y_i) = \frac{1}{\sqrt{2\pi\sigma}} \exp[-\frac{1}{2}(\frac{y_i - \mu_i}{\sigma})^2] \quad \text{for} \quad -\infty < y_i < \infty \qquad \text{(Eq. F-3)}$$

$$Var(y_i) = \sigma^2 \qquad \text{(Eq. F-4)}$$

Poisson Regression Model:

$$f(y_i) = \frac{\mu_i^{y_i} e^{-\mu_i}}{y_i!} \quad \text{for} \quad y_i = 0, 1, 2, \ldots \qquad \text{(Eq. F-5)}$$

$$Var(y_i) = \mu_i \qquad \text{(Eq. F-6)}$$

Negative Binomial Regression Model:

$$f(y_i) = \frac{\Gamma(y_i + 1/k)}{\Gamma(y_i + 1)\Gamma(1/k)} \frac{(k\mu_i)^{y_i}}{(1 + k\mu_i)^{y_i + 1/k}} \quad \text{for} \quad y_i = 0, 1, 2, \ldots \qquad \text{(Eq. F-7)}$$

$$Var(y_i) = \mu_i + k(\mu_i)^2 \qquad \text{(Eq. F-8)}$$

Where (for all three distributions),

y_i (response variable) = number of accidents per year at an intersection with mean μ_i

k = dispersion parameter

In Poisson models, the variability should be equal to the mean, as mean and the variance are identical for this distribution. However, when data has more variability or in other words data is over dispersed, than negative binomial distribution is more appropriate for modeling of data. As shown above the variance for a negative binomial distribution is given by $Var(y_i) = \mu_i + k(\mu_i)^2$, where k is dispersion parameter to take into account the more variability present in the data. When k = 0, the negative binomial distribution is equivalent to the Poisson distribution.

To further clarify,

The mean of number of accidents is given by

$$\mu_i = \exp(\sum_{j=1}^{k} b_j X_{ij}) \qquad \text{(Eq. F-9)}$$

Where y_i has Poisson distribution with following probability density function

$$f(y_i) = \frac{\mu_i^{y_i} e^{-\mu_i}}{y_i!} \quad \text{for } y_i = 0, 1, 2, \ldots \qquad \text{(Eq. F-10)}$$

Or y_i has negative binomial distribution with following probability density function

$$f(y_i) = \frac{\Gamma(y_i + 1/k)}{\Gamma(y_i + 1)\Gamma(1/k)} \frac{(k\mu_i)^{y_i}}{(1 + k\mu_i)^{y_i + 1/k}} \quad \text{for } y_i = 0, 1, 2, \ldots \qquad \text{(Eq. F-11)}$$