UPDATE:
A Detailed Investigation of Crash Risk Reduction Resulting From Red Light Cameras in Small Urban Areas

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16. Abstract

This is an update to the October 2003 version of this report. Using the latest available data, we include an additional 12 months of accident data. Additionally, several data coding errors were discovered in the original data set and corrected for this report. Therefore, results from the October 2003 report should be disregarded.

This paper analyzes the impact of red light cameras (RLCs) on crashes at signalized intersections. It examines total crashes and also breaks crashes into categories based on both severity (e.g., causing severe injuries or only property da7mage) and by type (e.g., angle, rear end). Prompted by criticism of the simplistic methods and small data sets used in many studies of red light cameras, we relate the occurrence of these crashes to the characteristics of signalized intersections, presence or absence of RLC, traffic, weather and other variables. Using a large data set including 26 months before the introduction of RLCs, we analyze reported accidents occurring near 303 intersections over a 57-month period, for a total of 17,271 observations.

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Executive Summary

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Prompted by criticism of the simplistic methods and small data sets used in many studies of red light cameras, we relate the occurrence of these crashes to the characteristics of signalized intersections, presence or absence of RLC, traffic, weather and other variables. Using a large data set, including 26 months before the introduction of RLCs, we analyze reported accidents occurring near 303 intersections over a 57-month period, for a total of 17,271 observations. Employing maximum likelihood estimation of Poisson regression models, we find that:

The results do not support the view that red light cameras reduce crashes. Instead, we find that RLCs are associated with higher levels of many types and severity categories of crashes.

An overall time trend during the study indicated that accidents are becoming less frequent, about 5 percent per year.

However, the intersections where RLCs were installed are not experiencing the same decrease. When analyzing total crashes, we find that RLCs have a statistically significant ($p<0.001$) and large (40% increase) effect on accident rates.

In addition, RLCs have a statistically significant, positive impact on rear-end accidents, sideswipes, and accidents involving cars turning left (traveling on the same roadway).

The one type of accident found to experience a decrease at RLC sites are those involving a left turning car and a car traveling on a different roadway.

When accidents are broken down by severity, RLCs were found to have a statistically significant ($p<0.001$) and large effect (40-50% increase) on property damage only and possible injury crashes. There was a positive, but statistically insignificant estimated effect on severe (fatal, evident, and disabling) accidents.

These results run contrary to the many studies in the RLC literature. Previous studies have sometimes found an increase in rear-end accidents, but often find offsetting decreases in other types of accidents. While this study incorporated many advances in methodology over previous studies, additional work remains to be done. Because accident studies rarely use a true experimental design and data are not perfectly observable, additional careful study of RLCs is warranted to verify our results.

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* We would like to acknowledge the assistance of the GDOT and Tony Ku of the NCDOT.

TABLE OF CONTENTS

TABLES

FIGURES

I. Introduction

1.1 Problem Statement

Nearly half of all accidents in the U.S. occur at or near intersections (US DOT, 1999, p. 50). Consequently, many studies have been conducted that relate various aspects of intersections to safety and accident rates to develop improvement strategies. One such strategy is automated enforcement of traffic signals using cameras, i.e., red light cameras (RLCs), which has been suggested and used in some cities to reduce red light running. The potential of these cameras in reducing accidents and improving safety have been reported in few studies, with most studies reporting mixed results. For example, Retting et al. (1999a), Retting and Kyrychenko (2002), and Milazzo et al. (2001), using before and after data found RLCs reduce crashes at intersections. On the other hand, Andreassen's (1995) longitudinal study spanning a 10-year period found reductions in crashes at high accident sites and increases in crashes at low accident sites. McFadden and McGee (1999) add another twist in their review of studies on automated enforcement of red light running. While accepting reductions in violations and cost savings as benefits, they suggested that improved methodology and more data are needed to validate and quantify the effects of RLCs on crashes, thus casting some doubts on prevailing views on the benefits of RLCs.

Despite McFadden and McGee's suggestion, no existing study carefully examines the characteristics of signalized intersections, weather, and accidents together to determine the role of RLCs in a comprehensive intersection-safety program. Similarly, there are few studies, if any, of RLCs that use extensive data including those for intersections that have no RLCs and that can be considered as control groups. Thus, there is still the need for studies of RLCs and their impacts on safety that control for environmental conditions and intersection characteristics. Without such a study, some of the claimed benefits of RLCs could be a result of inadequate modeling or artifacts of the methodologies used.

1.2 Objectives

Given the need for further studies on RLCs established above, the objective of this research is to analyze the impact of RLCs on red light violations and accidents in a holistic framework by accounting for the roles of intersection characteristics and environmental variables in such accidents, and that also account for changes in accidents at intersections with no RLCs. Because single policy changes do not occur in a vacuum, and because the characteristics of signalized intersections vary widely, policy makers and transportation engineers must be able to choose the most appropriate locations for RLCs. Simultaneously, this study identifies other variables that are associated with accident rates at signalized intersections.

1.3 Research Approach

Though the research methodology is described in detail elsewhere in this report, a brief summary is appropriate at this point. An extensive literature review was conducted to assess the existing knowledge on intersection safety, red light running, and the impacts of red light cameras. Thereafter, Poisson and negative binomial time-series regression models were developed to relate the characteristics of signalized intersections (including road characteristics and traffic volumes) and environmental conditions to the type and severity of accidents. The data on the characteristics were collected for all signalized intersections in Greensboro in collaboration with the Traffic Engineering Department of the City of Greensboro, as were data on traffic counts (average daily volume), signal timing, number of lanes, and other characteristics. From the North Carolina Department of Transportation (NCDOT), we obtained data for each signalized intersection on accident rates, types of accidents (e.g., rear-end collisions, front to side impacts), severity of accidents (e.g., crashes resulting in fatalities, possible injury, and property damage), and when the accidents occurred. Data on snowfall/ice and total precipitation were obtained from the National Oceanic and Atmospheric Administration. In addition, information on when the RLCs were placed at each intersection and the characteristics of these RLCs were collected.

A major finding uncovered in the preliminary data collection and analyses of NCDOT guidelines for RLC installation pointed to low amber times for several intersections with RLCs (compared to the minimum specified in the North Carolina state enabling legislation) that led to many red light violation tickets issued. This preliminary finding resulted in policy changes in Greensboro and its adjoining city, High Point, in terms of retiming some of the red lights at intersections with RLCs.

The analysis found that in contrast with previous U.S. studies on RLCs, signalized intersections had higher accident rates following the implementation of RLCs when compared to similar intersections. This finding is true for all but one category of accidents studied. Only for Left Turn, Different Roadway did we find a negative association between RLCs and accident rates. Given that this type of accident accounts for less that 3.6 percent of accidents overall and less than 2.5 percent of accidents at the RLC sites, this will have little effect overall. In most other cases, large, statistically significant increases in accident rates were found.

1.4. Choice of study area

Greensboro, North Carolina, in Guilford County, is located approximately 80 miles WNW of the capital, Raleigh. Interstates 85 and 40 pass through the southern part of the city. According to the 2000 Census, 223,891 of the county's 421,048 people live in Greensboro. In the county there were 333,534 vehicles registered to 298,732 licensed drivers in 1999 (Wiliszowski et al., 2001). The area has experienced a large amount of growth, with the city, county, and state seeing population increases of 21-22 percent over the last decade. There are 648.8 persons per square mile in the county, compared with 165.2 persons per square mile in the state as a whole. Greensboro is part of the Greensboro/Winston-Salem/High Point, North Carolina, Metropolitan Statistical Area.

Table 1.1: Example of Monthly Tickets Data

Street 1	Street 2	December 2001 Tickets Issued
Holden Road	Spring Garden Road	150
Wendover Avenue	English Street	69
Battleground Avenue	Brassfield Road	90
High Point Road	Pinecroft Road	312
Wendover Avenue	Church Street	138
Holden Road	Wendover Avenue	109
Randleman Road	Florida Street	12
Randleman Road	Creekridge Road	145
Battleground Avenue	Pisgah Church Road	232
Holden Road	McCuisition	72
High Point Road	Merritt Road	23
Church Street	Cone Blvd	9
Battleground Avenue	Cone Blvd	345
Wendover Avenue	Big Tree	86
Freeman Mill Road	Colisuem	34
Spring Street	Friendly Avenue	56
Wendover Avenue	Hill Street	228
Wendover Avenue	Bridford Parkway	39

The primary means of transportation in Greensboro is owner-occupied vehicles, with 79.1 percent of the transportation mode share involving driving alone and 12.5 percent carpooling (Greensboro City Data Book, 2001). The Greensboro Department of Transportation (GDOT) maintains 876 miles of roadway, while the NCDOT maintains another 236 miles, including the interstates, US-routes, and major state highways.

During the study period, there were 413 intersections controlled by traffic signals. According to the Greensboro Police Department, there were 498 accidents in 1999 classified as being caused by red light running.

Greensboro and its neighboring city of High Point contracted with Peek Traffic to install and operate their RLCs. The contracts were originally for three years[1] and specify a $50 civil fine for violations. Of this, the city is paid $15, with the remaining $35 retained by Peek Traffic. The first two cameras in Greensboro began operation on February 7, 2001, and citations were mailed out to offenders beginning February 15, 2001.[2] As of May 2002, there were 18 cameras operating, with plans for several more. Over the first year of the RLC program, the average number of tickets issued per camera, per day was 6.8, resulting in more than $1.2 million in fines.

Table 1.1 presents the monthly citations for December 2001 at each of the camera locations. The high variability in these numbers, ranging from 9 to 345 at two intersections on Cone Boulevard, suggests that the intersections are extremely heterogeneous regarding red-light-running behavior. While one might think that traffic volume accounts for most of these differences, the average daily traffic volume (ADV) of the lowest ticket and highest ticket

[1] As of June 2004, High Point renewed the contract, and Greensboro is on a month-to-month contract while it decides whether to renew.
[2] Because our data are grouped into monthly observations, and few tickets were issued until the end of February 2001, we treat March 2001 as the official start date of the program in our data analysis.

locations are 38,750 and 55,325 respectively. Thus, as much information as possible should be collected about these intersections to fully understand red-light-running behavior and accidents.

A concern of all safety advocates is that new safety programs, such as red light cameras, should be implemented in the most efficient manner possible. There have been some critics in Greensboro who worry that the locations of some cameras may not be chosen to maximize safety, but rather to maximize citations. Their evidence is of two types. First, it is generally not the city engineers who choose the placement of the RLCs. In High Point, the city "…developed a list of about 30 potential intersections, and PEEK Traffic officials *(narrowed)* that list to about 10 where the cameras *(were)* installed…" (Garber, 2000). Because Peek's contract specifies payment of $35 per citation and no compensation for accident reduction, the final decision regarding locations is not done with the proper incentives in mind.

As possible evidence of the inefficient location of RLCs, another newspaper article noted, "Of the 23 Greensboro intersections with the most accidents caused by red light violators, only four have cameras…" (Reese, 2002). While all such intersections may not be appropriate for red light cameras, it is understandable that one might wonder why more of these intersections were not targeted.

2. Review of Relevant Literature

This research project determines the role of RLCs in reducing accidents at intersections. Because of the nature of RLCs, the focus of the research will be on signalized intersections. To properly determine the causes of accidents at these intersections, it is necessary to review the literature on factors that influence intersection safety in general, review previous studies of red light running, and also review previous studies about the impact of RLCs on red light running and safety. Thus, the literature review is broken down into three sections as follows:

- Research on Intersection Safety
- Red Light Running
- Red Light Cameras

2.1. Research on Intersection Safety

Of the 6,394,000 automobile crashes in the U.S. in 2000, 44 percent occurred at intersections or were classified as “intersection-related.” Of these, 47 percent occurred at intersections with traffic signals (NHTSA, Traffic Safety Facts, 2000). The nature of intersections poses a special set of dangers for vehicles, pedestrians, and bicyclists. For vehicles, intersections are likely to involve dangerous “angle” crashes where little protection is given to drivers and occupants, and rear-end collisions where whiplash injuries are common. Approximately 22 percent of fatalities and 46 percent of injuries to pedestrians occur at intersections.

The Advocates for Highway and Auto Safety (2001) identified nine main ways to improve intersection safety:

1) Changes to or installation of appropriate static traffic control devices
2) Installing traffic signals
3) Proper timing of traffic signals
4) Installing dedicated turning lanes
5) Removing sight distance restrictions
6) Use of roundabouts
7) Use of Intelligent Transportation Systems (ITS)
8) Automated enforcement of red light running
9) Better signing such as larger, brighter stop, yield, and speed limit information

Within these nine suggestions are components that deal with structural changes, law enforcement, and conveying information to drivers. The standard protocol of most modern traffic-safety campaigns focuses on the “Three E’s”: Engineering, Enforcement, and Education.

Tarawneh et al. (2001) found that an education campaign significantly increased drivers’ understanding of traffic laws associated with red light running. However, the Insurance Institute for Highway Safety (IIHS) (2001) criticizes the role of education in increasing safety and believes that engineering and enforcement efforts are much more important.

Many times enforcement efforts are done on a high intensity, but discontinuous basis (often called a “blitz” approach). These efforts can significantly affect safety, but are too costly to be used continuously. However, a low level of targeted enforcement can have large benefits.

In Australia, several areas have been using Random Road Watch programs. These programs randomly monitor areas of roadway for two-hour periods of time, using marked patrol cars. The intensity of the effort is chosen at a level that can be sustained over the long run, and has been found to reduce accidents significantly, particularly fatal crashes (down 31%) (Newstead et al., 2001).

When analyzing strategies for safety improvements on roadways, one must first establish that a given strategy will produce the desired results. Occasionally, the goals of a safety program are measured in terms of compliance with the law. This is often the case with seatbelt programs, speed reduction programs, and child safety seat programs. However, the underlying goal should never be ignored, which is to reduce crashes and the resulting fatalities, injuries, and property damage.

Once a strategy is known to increase safety, good estimates of the extent of its benefits should be made for various types of its applications. The main purpose of quantifying the benefits is so that reasonably accurate studies of efficiency can be made. Except on social grounds, a strategy with known benefits is of no practical value if its costs exceed the benefits gained, or if a strategy with similar benefits can be implemented with lower costs. The most obvious benefits to a safety program are reductions in fatalities, injuries, and property damage. There are two ways that injuries and damages are assessed in accident records. The most common, the KABCO method, categorizes accidents and injuries as:

K: Killed
A: Incapacitating or Disabling Injury
B: Not Incapacitating, but Evident Injury
C: Possible Injury
O: No Injury, Property Damage Only (PDO)

Another accident severity scale used is the MAIS or Maximum Abbreviated Injury Score. It classifies accidents as follows:

Fatal
Critical (MAIS 5)
Severe (MAIS 4)
Serious (MAIS 3)
Moderate (MAIS 2)
Minor (MAIS 1)
No Injury (MAIS 0)

Under both methods, accident classification is somewhat subjective and normally determined by a police officer at the scene. In the present study, we use the KABCO system as reported in our accident data. To compare severity between different types of accidents, it is convenient to attach a dollar value to each type of accident or injury. In October 1994, the Federal Highway Administration (FHWA) issued a list of "Comprehensive Cost Estimates," listed in Table 2.1. These values were updated to 2002 dollars by the investigators of this project.[3]

Also listed in Table 2.1 are "Standardized Crash Cost Estimates for North Carolina," issued in December 2001, by the NCDOT (Troy, 2001). The values determined in this report are also termed "comprehensive," in that they include estimates of medical, work loss, employer costs, traffic delay, property damage, and changes in quality of life. Though these cost estimates were issued in 2001, they are measured in terms of year 2000 dollars.

Table 2.1: Comprehensive Costs, Each Occurrence (KABC Scale)

Severity	Description	FHWA (1994)	FHWA (2002)	NCDOT 2001
K	Fatal	$2,600,000	$2,979,600	$3,300,000
A	Incapacitating	180,000	206,280	200,000
B	Evident	36,000	41,256	57,000
C	Possible	19,000	21,774	27,000
PDO	Property Damage Only	2,000	2,292	3,900

In addition to accident reductions, other possible benefits or costs of implementing safety programs are changes in delays at intersections, resulting in effective increases or reductions in road capacity. These changes affect travel times for roadway users and should be counted properly in benefit/cost ratios. While reducing speed limits may increase safety but reduce capacity, there are some safety efforts that have also been shown to increase capacity. For example, efficiently programming traffic control devices in a network can yield benefits in reduced delays, and reduced fuel use, as well as increased safety (Skabardonis, 2001).

Another important consideration is that very few safety improvement projects are undertaken randomly, as would be required for an unbiased estimate of the effects. Most often, safety efforts are directed toward intersections or roadways that have the highest accident rates in a given time period. Ceteris paribus, an intersection with an unusually high accident rate in one period, is likely to have a lower (more average) rate in the next. This phenomenon is sometimes called the "regression to the mean effect." Thus, the effects of a safety program targeted in this way may be overstated. Kulmala (1994) found that accidents declined approximately 20 percent due to regression to the mean effects, independent of any safety measures implemented. If ignored, regression to the mean effects can easily mislead researchers to inappropriately attribute crash reductions to an ineffective safety program.

In addition, the quality of the data used in safety studies must be ascertained. One often overlooked aspect of accident data is censoring. One must realize that not all accidents are reported, and state laws differ on reporting requirements. In North Carolina, the crash-reporting threshold is currently $1000. That is, if a police officer is called to the scene of an accident, the officer is not required to make a report of the details of the accident unless he or

[3] Updated using GDP Implicit Price Deflator from 01, 2002.

she is certain that the damage is in excess of $1000. Therefore, many accidents are never entered into a crash database and may affect the results of accident studies if ignored. The research related to this subject has been sparse. Zegeer et al. (1998) studied the differences in various types of accidents that would be reported under three different types of reporting thresholds: traditional (value), tow away, and injury. They found that using higher thresholds (tow away versus traditional, for example) tends to seriously underreport certain types of crashes. One would expect that the traditional thresholds lead to similar types of bias in accident reporting.

2.2. Red Light Running

While installing red lights at intersections can often improve safety and traffic flow, such intersections are often studied because they are the scenes of many devastating crashes. Retting et al. (1995) found that running traffic control devices were the primary cause of 22 percent of all crashes and 27 percent of injury crashes. They also found that crashes involving red- light running are more likely to involve an injury, occurring in 45 percent of these crashes.

Given the danger associated with running red lights, a question one asks is, “Why would an individual do this?” Wissinger et al. (2000) discovered that the main reason people purposely run red lights is to minimize delay because they are in a hurry. In addition, Wissinger found that many people do not properly understand the law regarding red light running, which varies by state. In North Carolina, the law states:

> *“Vehicles facing a red light controlling traffic passing straight through an intersection from a steady or strobe beam stoplight shall not enter the intersection while the steady or strobe beam stoplight is emitting a red light controlling traffic passing straight through an intersection…” (NCGS 20-158 (b) (2)).*

Because many intersections contain “stop bars,” many motorists believe that their vehicle must pass the stop bar before the light turns red. However, as the law above states, it is the intersection, i.e. the curb, that is important for making a legal maneuver. Thus, vehicles may inadvertently violate the letter of the law by stopping on a stop bar that extends beyond a curb.

In addition, some drivers may run a red light because of poor signal timing. At some intersections, it has been found that so-called “dilemma zones” exist. A dilemma zone exists when a reasonable and prudent driver can neither stop the vehicle in time nor enter the intersection before the onset of a red light. Setting amber times too low, based on speed, visibility, and grade of the intersection, causes dilemma zones. For example, a vehicle 250 feet from an intersection may require 300 feet to stop and 4.5 seconds to reach the intersection. If the amber time is less than 4.5 seconds (plus some increment for reaction time), the driver has no ability to stop, and will run the red light. In these cases, a simple solution to improve intersection safety is to increase the amber time.

However, when we want to increase safety at intersections with red lights, it is important to understand the various types of drivers, circumstances, and causes of red light running. Milazzo, Hummer, and Prothe (2001) carefully classified red light running in several ways. First, they characterized drivers into four types:

1) Reasonable/Prudent: an attentive, cautious driver
2) Inattentive: may be distracted by children in the car, cell phone, or other reasons
3) Reckless: does not show proper regard for their own or others' safety
4) Mistaken (Judgment Error)

They then characterized the reasons why someone may or may not stop:

1) Enforcement measures: risk of receiving a ticket
2) Risk of crash
3) Time savings

Finally, for drivers who enter an intersection, Milazzo et al. (2001) classify each driver by answering the following questions about the maneuver:

1) Is it *safe*?
2) Is it *legal*?
3) Is it *intentional*?

The answers to these questions determine the type of behavior exhibited by the driver, why a maneuver is performed, and what can be done to increase safety. Breaking down drivers in this way creates reasonable pictures of different types of drivers, and this information can be used to predict the effect of safety improvements on them. For example, an inattentive driver may not avoid running a red light because of increased enforcement measures, but may respond to more visible signage.

Porter and Berry (1999) used surveys to form a profile of those drivers who run red lights, identifying a red light runner as a younger person who is driving alone and often in a hurry. While this profile is at first appealing, it is certainly not wholly inclusive of the 56 percent of respondents to the survey who admitted to running red lights, and one in five who admitted running at least one out of the last 10 red lights encountered prior to the survey. When asked why drivers stop for a red light, 69.3 percent responded because it is safer, compared to only 15.4 percent who stop because it is illegal.

While driver characteristics are undoubtedly important, the characteristics of the intersections themselves can significantly impact red light running and the resulting crashes. Stimpson, Zador, and Tarnoff (1980) and other research has found that simply re-timing stoplights significantly increases safety. They found that increasing the amber time by approximately 30 percent reduces the number of vehicles that enter an intersection in conflict[4] by 90 percent. Because signal-timing changes are very inexpensive and have potential for large safety benefits, it could be argued that it should be the first issue addressed concerning red light running. Retting, Chapline, and Williams (2002) found that 40 out of 51 sites examined in New York State required timing adjustments. They found that doing so reduced crashes at these intersections by approximately 5 percent. Furthermore, Retting et al. (2002) found that

[4] Vehicles that spent a minimum of 0.2 seconds in an intersection after the onset of red.

traffic volume, number of lanes of traffic, and the use of fully actuated signals were all associated with higher number of accidents. They also found that fully actuated signals may increase accidents because they are often located in suburban, non-networked, high-speed locations.

Thus, many studies have investigated different aspects of who runs red lights and why, the associated danger, and possible intersection characteristics that can affect the magnitude of the danger. However, much work is still to be done to evaluate the myriad of options for continuing improvement of intersection safety. Proper timing of signals or the removal of unwarranted signals (Retting, Williams, and Greene, 1998) can be considered a low-cost approach, while increasing the fines and other sanctions against drivers who run red lights can be effective. Increased enforcement, coupled with education campaigns, may also help to mitigate the danger. However, traditional law enforcement methods can actually cause accidents at intersections. For example, if an officer observes a vehicle running a red light, issuing a citation often requires the officer to follow the offender through the light, creating additional danger to motorists. One solution is to mount a so-called “rat box” on the backside of traffic signals. These rat boxes contain light emitting diodes, which activate when the signal turns red. This type of system allows an officer stationed downstream from the signal to more safely observe and cite offenders.

Recently, in many municipalities, interest has been increasing in automated enforcement mechanisms, particularly for red light enforcement. We will describe this technology and the existing research in the next section.

2.3. Red Light Cameras[5] and Previous Studies

A red light camera (RLC) system typically employs electromagnetic loops and a pole-mounted camera (either 35 millimeter or digital) that are tied into the timing system of a traffic signal. Because the camera’s position is fixed, only one direction of traffic flow is monitored at an intersection. Once the signal changes to red, the system is generally programmed with a small “enforcement tolerance” of 0.1 to 0.3 seconds, after which any vehicle crossing the loops will trigger the camera unit to take two photographs. To establish evidence of a violation, the first photograph captures the vehicle as it enters the intersection, and the second captures the vehicle’s progress into the intersection. The photographs must be of sufficient resolution to allow identification of the license plate of the vehicle.

Typically, these photographs are reviewed by a police official to screen out those taken of funeral processions, emergency vehicles, etc. In Greensboro only 40.3 percent of the “events” captured by RLCs during the first year of operation resulted in tickets being issued.

RLCs are an attractive option for municipalities for several reasons. Normally, an outside contractor who offers to install and operate the system with no up-front cost to the local government approaches municipalities. These contractors earn a commission on each ticket issued, with the remainder going to the municipality. In addition to being a revenue source, the municipalities see increased safety as a benefit of RLCs.

Thus far, the safety benefits of RLC programs have not been convincingly shown. Although several studies have shown that RLCs usually reduce the rate of violations (Retting et al. 1999a, Retting et al. 1999b), very little evidence exists that confirms that RLCs reduce

[5] A good overview of RLC technology and implementation in North Carolina is found in Milazzo, Hummer, and Prothe (2001). For the sake of brevity, we only outline the major ideas here.

accident rates. Many studies and reports[6] have consistently shown that in short periods after RLC programs are implemented, violation rates drop dramatically. Various programs have seen reductions in violations of between 20 percent and 83 percent as drivers become accustomed to the presence of the cameras and are educated by the signs and public information campaigns that usually accompany RLC programs. In Greensboro, the violation rate declined by roughly 35 percent within several months. The few known studies that find reductions in accident rates in the U.S. were conducted using data from Oxnard, CA (Retting and Kyrychenko, 2002), Fairfax, VA (Retting et al. 1999a), and Charlotte, NC (Milazzo et al., 2001). Most of these studies compare crash totals for a period before and after the introduction of RLCs. While the number of crashes at intersections with RLCs declined, results varied drastically based on the type of crash. Overall, crashes went down 7 percent in Oxnard, and 8 percent in Charlotte. However, front-into-side crashes reportedly went down by 32 percent in Oxnard. This fact highlights the importance of a detailed investigation of possible crash reductions by type and severity.

A ten-year study in Australia (Andreassen, 1995), five years both before and after the introduction of RLCs, found no overall decrease in accidents from RLCs. This study found evidence of the regression to the mean effect, with low accident sites experiencing more accidents and higher accident sites seeing a decrease. When compared to intersections without RLCs, a small reduction in pedestrian accidents was observed after RLCs were introduced. Offsetting this reduction in accidents was a significant increase in front-into-side crashes and in rear-end collisions (approximately double).

It has been suggested that reductions in violations translate into increased safety. As introduced previously, Milazzo et al. (2001) point out that there are many different types of red light runners and red light running. To simplify, we can think of two broad categories of red light running, low risk and high risk. Milazzo et al. reviewed 34 photographs of crashes captured by red light cameras and found that all of the crashes caused by red light running involved vehicles entering the intersection more than 1.0 second after the onset of red, and the large majority entered the intersection more than 3.0 seconds after the onset of red. Thus, it appears that those who run red lights soon after the onset of red and before conflicting traffic has entered the intersection pose little risk of causing an accident.[7] Though this type of red light running is clearly illegal, one may argue that a reasonable, prudent, and attentive driver may occasionally risk entering an intersection in this short-time window. Those drivers who enter an intersection more than one second after the onset of red can broadly be labeled as reckless, inattentive, or mistaken.

Winn (1995) found that approximately 70 percent of RLC violations occur between 0 and 1 second after the onset of red and approximately 29 percent between 1 and 5 seconds. After the RLC program went into effect, the number of violations occurring between 0 and 5 seconds dropped by nearly two thirds. The most dangerous violations, those occurring more than 5 seconds into the red phase, did not drop in the three-year period after the program began issuing tickets. Thus, we see the potential problem in the connection between RLCs and safety. The reckless or inattentive (and most dangerous) red light runners seem to respond least to an RLC program.

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[6] See Maccubbin, Staples and Salwin, 2001 for an extensive list.

[7] In our dataset, the average "all red clearance time" before opposing traffic sees a green signal is 1.55 seconds.

However, there are many anecdotal reports and several formal studies that demonstrate decreases in accidents after RLC programs are implemented. These studies give estimates of crash reductions ranging from 0 percent to 70 percent for angle crashes and changes in rear end collisions ranging from a decrease of 22 percent to an increase of 50 percent.[8] The large range of values seen in these reports raises several questions about the results:

1) Are these numbers controlling for other safety improvements, programs, and changes in automobile safety features that occur along with RLC programs?
2) Are there some intersection characteristics that may influence the effectiveness of RLCs in increasing safety?
3) Are these changes biased because of regression to the mean effects?
4) Are the effects of the cameras limited to monitored intersections or are there some spillovers?

Previous reviews of the literature on RLCs and safety have been done. McFadden and McGee (1999) performed a "Synthesis and Evaluation of Red Light Running Enforcement Programs in the United States." While they concluded that RLCs probably decrease violations between 20 and 60 percent, they suggested "additional crash data . . . to validate and quantify the RLR automated enforcement programs implication on crashes" (p. 27). Part of their concern was that "simple comparisons are not statistically rigorous to conclude that the RLR program will result in crash reduction immediately or in the long run" (p. 27).

More recently, Maccubbin, Staples, and Salwin (2001) performed an extensive review of the current evidence. They write:

> Each of the existing independent analysis makes an attempt to assess the long-term impacts of a system that is affected by a variety of external influences that can also impact traffic safety. This is a characteristic of traffic safety impact studies that is probably difficult to overcome. While a long-term study may provide a better indication of any lasting impact of the systems on intersection safety, this longer time frame also allows a greater opportunity for other, necessary, improvements that can also impact safety, such as intersection and pedestrian safety improvements. The result is that the safety impact of the camera systems remains unclear.

Though it is impossible to perform a perfect evaluation of the impact of RLCs, the existing research is lacking in many fundamental ways. Zaidel (2002) uses meta-analysis of several studies to suggest a "best estimate" of the effects of RLCs of an 11 percent reduction in accidents. However, he suggests that most of these studies fail to control for changes in design standards, biased selection of sites, and other safety improvements. Studies that do attempt to control for these types of changes (Andreassen, 1995; Kent et al., 1995) have found that RLCs provide no significant safety improvement. Flannery and Maccubbin (2002) also point to a lack of high-quality studies performed in the U.S., finding only two studies which used data on individual intersections along with usable crash data and traffic-count data.

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[8] See Maccubbin, Staples, and Salwin (2001) for an extensive summary of these estimates.

One of the most frequently cited papers that finds a decrease in crashes associated with an RLC program is by Retting and Kyrychenko (2002). This study uses 29 months of data before and after the implementation of 11 red light cameras in Oxnard, California. The study claims to use 16 observations and 12 dummy explanatory variables. Because only 16 observations were used, the authors provided a list of the data in the paper. This is reproduced in Table 2.2 below. The table of results from Retting and Kyrychenko's paper is reproduced in Table 2.3.

Table 2.2: Total Crashes Before and After Enforcement

City	Type of Intersection	Before	After	Percent Change
Bakersfield	Non-signalized	760	753	-0.9
Bakersfield	Signalized	771	739	-4.2
San Bernardino	Non-signalized	1220	1283	5.2
San Bernardino	Signalized	1,324	1400	5.7
Santa Barbara	Non-signalized	712	622	-12.6
Santa Barbara	Signalized	488	438	-10.2
Oxnard	Non-signalized	994	1,011	1.7
Oxnard	Signalized	1,322	1,250	-5.4

Table 2.3: Estimated Effects on Total Crashes

Effect	Degrees of Freedom	Mean Square	F-value	p-value	Estimate	Percent Reduction
Camera	1	0.0013308	11.33	0.0281	-0.07296	7
Error	4	0.00011741				

There are several serious problems with this analysis. Firstly, the fact that only aggregate data are used for four towns, ignoring such important variables as traffic counts and the numbers of the various types of intersections involved, is troubling. The study period was from January 1995 through December 1999. During the 1990s the four towns in the study grew at very different rates, seeing population changes from 7.89 percent (Santa Barbara) to 41.32 percent (Bakersfield). At a minimum, adjustments to the crude accident counts should have been made for these large variations in population growth.

Secondly, if the analysis is performed as Retting and Kyrychenko described (see appendix), 16 observations and 12 dummy variables leave 3 error degrees of freedom. Replicating the analysis reportedly done, one should end up with the following:

Table 2.4: Estimated Effects on Total Crashes: Corrected

Effect	Degrees of Freedom	Mean Square	F-value	p-value	Estimate	Percent Reduction
Camera	1	0.0013308	8.59	**0.0610**	-0.07296	7
Error	3	0.00015493				

It is striking how the Estimate and Mean Square are identical to those reported by Retting and Kyrychenko; however, the degrees of freedom and p-value have changed.[9]

[9] After sending emails to both Retting and Kyrychenko about this matter, we were told that they didn't remember why there were 4 error degrees of freedom, but that they probably left out one of the dummy

Third, the analysis performed does not do what the authors claim. The authors believed that they were using the three cities in California other than Oxnard as controls in an analysis of variance. Using the 12 dummy variables in the manner they described reduces the estimate to a trivial calculation. First, the crash counts in Table 2.2 were converted to natural logarithms. As shown in the appendix, the "generalized linear regression" estimate of -.07296 is simply calculated as follows (where *S* and *NS* are signalized and non-signalized):

$$\begin{aligned} Estimate &= [\ln(OXN_{SAFT}) - \ln(OXN_{SBEF})] + [\ln(OXN_{NSBEF}) - \ln(OXN_{NSAFT}] \\ &= [7.13090 \quad - \; 7.18690 \quad] + [\; 6.90174 \quad - \; 6.91870 \quad] \\ &= \; -0.05600 \quad -0.01696 \quad = \; -0.07296 \end{aligned}$$

Recalling that taking the difference between two natural logarithms is equivalent to calculating the percentage difference between two numbers, all that is being done is to subtract the 1.7% from the -5.4% in Table 2.3. The numbers used are slightly different because instead of using the starting number as the base for the percentage difference, the natural logarithm method uses the midpoint as the base.

The overall implication is that the effect attributed to the red light cameras by Retting and Kyrychenko is only a comparison of the accident growth rate between signalized and non-signalized intersections in Oxnard, CA. The other data does not act as a control, nor does it add any information to this model. This lack of control is especially critical for this study done in California because several important policy changes were implemented in the state during the period of the study. Most importantly, the fine for red light violations was increased from \$104 to \$270. In addition, the graduated licensing program for minors was expanded, significantly limiting the minors' driving privileges. Because of the way this model was constructed, the p-value calculated has no statistical meaning, and the estimate cannot be described as an effect of red light cameras.

variables. Running 12 regressions, leaving one dummy variable out each time suggested that this was not the case.

3. Data Collection

To successfully analyze how red light cameras interact with other roadway characteristics to impact safety, three different types of data were collected. The first type concerned information about the physical properties of each signalized intersection in Greensboro, the second involved the cameras themselves, and the third concerned accidents at signalized intersections. The data and collection methods are described in the following sections.

3.1. Intersections

The scope of the data collection was limited to intersections with stoplights. In addition, we eliminated stoplights that were located on highway exit ramps to obtain a more homogeneous data set. These data were collected in collaboration with the Greensboro Department of Transportation (GDOT). Initial data collection efforts showed that the GDOT did not have a formal data set describing the characteristics of intersections. Thus, it became necessary to collect as much data as possible from technical drawings of these intersections. It was discovered that some of the signalized intersections from the list of 413 provided by the Engineering Department of GDOT had no drawings and many drawings were incomplete. Furthermore, some of the data provided by the Traffic Signals Maintenance division were inconsistent with those from the Engineering Department, thus requiring a large amount of time and effort for data collection, reconciliation, and cleaning. Site visits were made to some intersections to ensure completeness and accuracy of the data, and the knowledge of many GDOT officials was used to fill in missing values.

The collected data set consists of descriptive features of 303 intersections. These features include amber timing for each road, all red timing, posted speed limits, and number of lanes on each road. Others are the number of left turn lanes on each road, the presence of dedicated right turn lanes, sidewalks, one-way or two-way street, “Left Turn Must Yield on Green” signs, “No Right Turn on Red” signs, and “No Left Turn” signs. Other characteristics on which data were collected are the presence of solid medians at intersections, left turn arrow, and pedestrian crossing signals.

In addition, the average daily traffic volume (ADV) at each intersection was provided by GDOT for the years 1990-2003. Ideally, measurements of ADV would be available for each intersection monthly. However, the GDOT collects this data for each intersection on a rotating basis, measuring each intersection approximately every two to three years. Therefore, a decision had to be made as to its treatment because the most recent ADV measurements were from 1998-2003, depending on the intersection. Upon examination, the data did not exhibit an obvious trend over time, especially if one focused only on the five years relevant to this study. Rather, the measurements appeared to be random observations of a stationary series. A possible explanation is that the various recorded traffic volumes were measured during different times of the year or days of the week. To even out the randomness in the recorded traffic volumes, the average ADV over all available observations for each intersection is used in the analysis.

The final descriptive data concerns the location of the intersection. GDOT’s GIS Department assisted in automatically matching approximately 80 percent of the intersections using ARCGIS. The rest were matched manually using MapInfo.

3.2. Red Light Cameras

We obtained the locations of Greensboro's red light cameras, dates of operation, and the number of tickets issued in each month for each camera. Here, a distinction between the number of "events" at a red light camera and the number of tickets issued is important. Many events trigger the camera to take a snapshot, but not all events result in a ticket being issued. In many cases, a person reviewing the snapshot determines that a violation did not occur. Other times a violation may have occurred, but a ticket was not issued because the license plate of the vehicle was obscured or could not be read, or the vehicle was in a funeral procession. This has resulted in a 40.3 percent red light ticket issuance rate in Greensboro.

The appeals process is also noteworthy. In Greensboro, five lawyers take turns hearing appeals from ticketed drivers and are compensated $37.50 per appeal, regardless the outcome. Any compensation made comes out of the city's $15 share of the $50 ticket. In the first 16 months of the red light camera program, 1,244 tickets were appealed and approximately 24 percent were successful (Fuchs, 2002).

Since the data on accidents are grouped by month, we constructed a dummy variable for each intersection to show the presence or absence of a red light camera each month. The analysis spans 57 continuous months; the first red light cameras were operational beginning in the 27th month. Several cameras became operational close to the end of the months they were installed. For these cameras, their initial dates of operation were pushed to the following month.

3.3. Accident Data

In North Carolina it is the duty of the Safety Information Management and Support Section of the North Carolina Department of Transportation (NCDOT) to collect data on accidents. They are responsible for acquiring and compiling accident data from police reports and entering them into a computerized database called the "Traffic Engineering Accident Analysis System" (TEAAS). This is a modern database created in 1999 using Java for web accessibility, Oracle for database functions, and CORBA to allow many different platforms to access it. A limitation of this data is that a police report is only filed when an accident is estimated to have involved more than $1,000 in damages or an injury (See attachment 1, North Carolina Accident Report). This monetary limit may cause problems with censoring some types of accidents more than others. For example, angle accidents may normally cost more than $1,000, while many low-speed rear-end accidents may cost less than $1,000 and are unreported. Figure 1 is a histogram of the total damages estimated by the police report for the accidents in our study. Note the very small percentage of accidents reported that have low estimated damage amounts. The labels on the x-axis are to be interpreted as "less than or equal to this amount, but greater than the previous category." There were 107 accidents with recorded damages of zero. Upon closer inspection of these records, it appears that sometimes some values in the police report are left blank; therefore, it is likely that many of these zeros are actually the result of missing values.

Figure 1: Damage Histogram

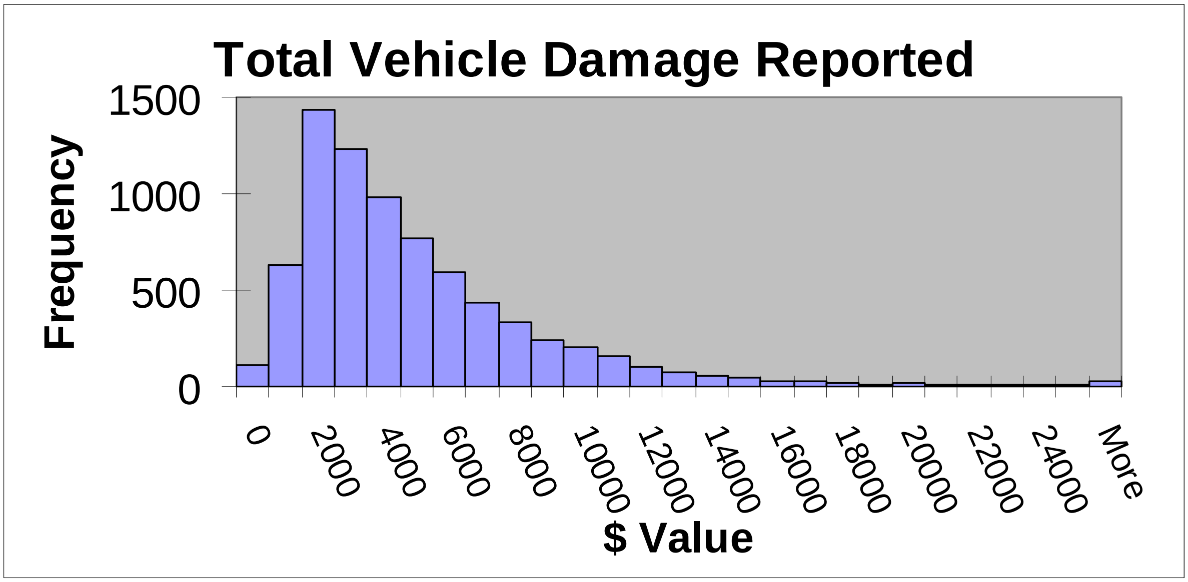


Table 3.1: Descriptive Statistics: Type of Crash vs. Severity

Crash Type	Severity Index						
	Fatal	A INJ	B INJ	C INJ	PDO	UNK	Total
ANGLE	8	38	395	1350	1928	6	3725
REAR END, SLOW OR STOP	--	6	106	1494	1780	4	3390
LEFT TURN, SAME ROADWAY	2	15	118	393	583	3	1114
SIDESWIPE, SAME DIRECTION	--	--	14	77	520	7	618
LEFT TURN, DIFFERENT ROADWAYS	1	2	36	128	216	--	383
FIXED OBJECT	1	5	38	72	160	21	297
HEAD ON	2	2	31	55	56	2	148
REAR END, TURN	--	--	7	46	79	1	133
BACKING UP	--	--	1	10	106	--	117
RIGHT TURN, SAME ROADWAY	--	--	2	21	88	--	111
RIGHT TURN, DIFFERENT ROADWAYS	--	--	4	22	66	--	92
PEDESTRIAN	4	10	34	33	7	--	88
SIDESWIPE,OPPOSITE DIRECTION	--	--	7	20	55	1	83
RAN OFF ROAD - RIGHT	--	--	11	22	44	1	78
PARKED MOTOR VEHICLE	--	--	2	10	36	11	59
OVERTURN/ROLLOVER	1	--	16	15	10	1	43
PEDALCYCLIST	--	5	17	17	--	--	39
RAN OFF ROAD - LEFT	--	1	5	10	20	3	39
MOVABLE OBJECT	--	--	2	7	20	4	33
UNKNOWN	--	--	1	14	17	1	33
ANIMAL	--	--	2	4	24	--	30
OTHER COLLISION WITH VEHICLE	--	--	6	8	16	--	30
RAN OFF ROAD - STRAIGHT	--	--	1	8	11	--	20
OTHER NON-COLLISION	--	--	7	8	2	--	17
JACKKNIFE	--	--	--	--	1	--	1
Grand Total	19	84	863	3844	5845	66	10721

Table 3.2: Descriptive Statistics

Descriptive Statistics: 303 intersections for 57 months = 17,271 observations					
Description	Variable	Mean	Std.Dev.	Minimum	Maximum
Month code	MONTH	29.000	16.452	1	57
Presence of RLC	RLCPRES	0.029	0.168	0	1
Number of left turn lanes	TOTLTL	1.640	0.859	0	4
Number of other traffic lanes	TOTLN	6.490	2.231	2	13
Presence of right turn lane	DEDRTL	0.446	0.497	0	1
Sidewalks	SWLK	0.432	0.495	0	1
Solid median	SLDMED	0.175	0.380	0	1
Pedestrian crossing signal	PEDSIG	0.257	0.437	0	1
Inches of snow	SNOW	0.409	1.477	0	8.2
Inches of Liquid Precipitation	PRECIP	3.645	2.226	0	9.98
All red time, street 1	ST1RED	1.550	0.552	0	5
All red time, street 2	ST2RED	1.542	0.525	0	5
0=1 way, 1=two way street	ST1FLOW	0.911	0.285	0	1
0=1 way, 1=two way street	ST2FLOW	0.861	0.346	0	1
Amber: actual-recommended	AMBD1	0.569	0.454	-1.555	2.475
Amber: actual-recommended	AMBD2	0.567	0.451	-1.015	2.175
Posted speed limit, street1	ST1SP	34.669	5.434	20	55
Posted speed limit, street2	ST2SP	34.868	5.681	20	55
Average daily volume	ADV	27952	12753	6774	69233
Natural Log of ADV	LOG(ADV)	10.134	0.465	8.821	11.145

The data are primarily contained in two types of files: the event level data contains one record for each accident, including location, number of vehicles involved, numbers of injuries by severity, and other data, and the unit level data contains one record for each vehicle involved in each accident. Each record details the type of vehicle, damage estimates, injury levels, indications of use of alcohol or seatbelts, and many other variables. We performed a query of this database, pulling all records that met the following conditions: First, the accidents must have occurred between 1/01/99 and 9/30/03.[10] This gives at least 26 months of "before" data and 22-31 months of "after" data.[11] Second, the accident must have occurred within 100 feet of the center of an intersection. The rationale for this limit is to avoid the influences of traffic from minor roads entering the main road. The last condition is that the accident must have occurred in Greensboro, North Carolina.

This query produced approximately 30,000 events with approximately 60,000 vehicles involved. However, only the records matching to one of the 303 intersections in this study were used. Records from the accident database were carefully checked for misspellings (e.g., Creekridge/Creek Ridge/Creekrige) or the use of alternate road names (e.g., Bryan Boulevard/Joseph M. Bryan Boulevard/Bryan Ave.). In the final data, 10,721 accidents were identified over the 57 months of the study at the 303 intersections. Since a balanced panel data set is used, the total observations are 17,271.

3.4. Other Data

To account for differences in weather, we used snowfall and total liquid precipitation amounts, as measured at the Piedmont Triad International Airport in Greensboro (NOAA 2004). Furthermore, the actual amber timing of each signal was compared to a recommended minimum amber timing based on the speed on the roadway. The difference between the actual and the recommended timing is used in the study. As discussed in Milazzo, Hummer, and Prothe (2001), the minimum safe amber timing is given by:

$$Y \geq t + \frac{v_o}{2a}$$

In this equation, Y is the minimum yellow time, t is the reaction time (typically assumed to be 1.0 second), v_o is the initial velocity of the vehicle in feet per second, and a is the deceleration rate, typically assumed to be 10 feet/sec^2. Using this formula, the difference between the actual and calculated amber time was calculated. A positive value indicates that an intersection has a longer amber time than the minimum recommended, which has been shown in several studies to reduce accidents (for example, Retting, Chapline, and Williams (2000)).

Tables 3.1 and 3.2 show the summary statistics for the data. In Table 3.1, a cross tabulation of the accident events is presented by type and severity. In the data analysis, we will examine total accidents both by type and severity. To avoid problems that occur when studying extremely rare events, we only study the five most frequently occurring types of accidents individually. These are angle crashes, rear ending a slowing or stopped vehicle, left turning vehicle struck by a second vehicle on the same roadway, left turning vehicle struck by a second vehicle on a different roadway, and a sideswipe by a vehicle on the same roadway. All other types of accidents are combined into the category "Other."

[10] The latest available at the writing of this report.
[11] Because the cameras were installed between 27 and 35 months after January 1999.

Similarly, we investigate the factors influencing the severity of accidents. Again, because fatalities and severe injuries (Type A) occurred so rarely in the data set, they are grouped together with evident, non-disabling injuries (Type B) into a category called “Severe.” In addition, we examine possible injuries (Type C) and accidents with no injuries (Property Damage Only) separately for comparison. Table 3.2 presents descriptive statistics for the explanatory variables in the study. Many characteristics of each intersection were recorded, as described above in Section 3.1.

4. Empirical Model

Conceptually, the design of this analysis is an expanded before/after model. A basic version of such a model compares the rate of accidents before the installation of a red light camera with the rate after installation. Over the data period of 57 months, 18 red light cameras were installed at intersections between 27 and 35 months into the time series. Examining only the monthly rates of accidents at these 18 intersections by severity before and after the installation of RLCs generated the descriptive statistics in Table 4.1.

The entries in the table represent the number of crashes *per 10 month period*. Thus, for camera number 01, before the red light camera installation there were approximately 23.46 accidents every 10 months. After the RLC was installed, there were approximately 24.83, a 5.8 percent increase. The changes in accident patterns varied dramatically, ranging from a 30.8 percent decrease to a 68.8 percent increase. On average, the results show a 2.5% decrease in accident rates.

Table 4.1: Before/After Statistics for 18 RLC Sites

	RLC Sites: No RLC Normalized/10 months						RLC Sites: With RLC Normalized/10 months						
ID #	**FTL**	**AINJ**	**BINJ**	**CINJ**	**PDO**	**Total**	**FTL**	**AINJ**	**BINJ**	**CINJ**	**PDO**	**Total**	**%Chg**
01	--	--	2.31	10.00	11.15	23.46	--	0.34	1.72	9.31	13.45	24.83	5.8%
02	--	0.38	1.92	9.62	6.54	18.46	--	--	0.34	9.31	8.97	18.62	0.9%
03	--	--	2.69	1.92	7.31	11.92	0.34	--	1.72	2.76	7.24	12.07	1.2%
04	--	0.38	1.15	4.23	10.00	15.77	--	0.34	1.38	9.31	10.00	21.03	33.4%
05	--	--	3.21	5.36	6.79	15.36	--	0.37	0.37	8.52	16.67	25.93	68.8%
06	--	--	1.85	7.41	7.41	17.04	--	0.36	0.36	8.21	9.29	18.21	6.9%
07	--	0.37	1.11	6.30	1.85	9.63	--	--	1.07	5.00	2.50	8.57	-11.0%
08	--	--	0.36	6.79	10.36	17.50	--	--	1.85	4.07	7.41	13.33	-23.8%
09	--	--	0.33	4.33	9.33	14.00	--	--	--	1.60	10.00	11.60	-17.1%
10	--	--	--	1.03	1.03	2.07	--	--	--	0.38	1.15	1.54	-25.6%
11	--	--	2.07	6.55	12.07	20.69	--	--	2.31	5.77	6.92	15.38	-25.6%
12	--	--	0.67	5.33	6.33	12.33	--	--	1.20	4.00	7.60	12.80	3.8%
13	--	0.32	0.65	4.52	6.13	11.61	--	--	0.83	5.00	10.00	15.83	36.3%
14	--	--	0.86	9.71	20.29	30.86	--	--	--	6.00	19.00	25.00	-19.0%
15	--	0.30	1.52	4.24	5.76	11.82	--	--	0.45	3.18	4.55	8.18	-30.8%
16	--	--	1.52	3.64	5.76	10.91	--	0.45	0.45	3.64	6.82	11.36	4.2%
17	--	--	2.50	5.31	10.63	18.44	--	--	0.43	13.91	15.65	30.00	62.7%
18	--	0.32	1.61	7.74	13.87	23.55	--	--	1.25	15.00	12.92	29.17	23.9%
Total	--	0.11	1.44	5.78	8.63	15.99	0.02	0.10	0.84	5.95	8.66	15.59	-2.5%

If one were to use the naïve approach shown in table 4.1, one would reasonably conclude that there has been a very small drop in accident rates that is possibly due to random fluctuation rather than the red light cameras.

Table 4.2: RLC Sites Before and After the RLC Program: Common Types of Accidents												
	First 29 months of data						Last 28 months of data					
CRASH TYPE	FTL	AINJ	BINJ	CINJ	PDO	Total	FTL	AINJ	BINJ	CINJ	PDO	Total
REAR END, SLOW OR STOP	--	1	17	152	188	358	--	1	6	172	201	380
ANGLE	--	2	34	78	115	229	--	2	15	82	124	223
LEFT TURN, SAME ROADWAY	--	1	7	29	44	81	--	--	5	16	26	47
SIDESWIPE, SAME DIRECTION	--	--	2	4	37	43	--	--	--	10	37	47
LEFT TURN, DIFFERENT ROADWAYS	--	--	6	13	15	34	--	--	2	1	3	6
REAR END, TURN	--	--	--	5	10	15	--	--	1	1	11	13
TOTAL (including omitted categories)	--	6	78	302	454	840	1	5	40	299	432	777

In Table 4.2 we show a simple comparison of how accidents varied between the first and second halves of the study (first 29 months vs. last 28 months). Because the RLCs began operation in the 27th month, the division is not perfectly accurate, but instructional nonetheless. The column totals are greater than the sum of the listed numbers, as they include other types of accidents not listed in the table (e.g., head on). Similar to other studies, we see an increase in rear end accidents. However, we see a large percentage decrease in both types of left turning accidents. Interestingly, we see no real change in angle accidents (229 vs. 223); these accidents are often cited as the type that should decrease most when RLCs are installed. Adjusting for the fact that the first period includes 29 months and the second 28, we actually see a small increase in angle accidents (7.90 per month to 7.96).

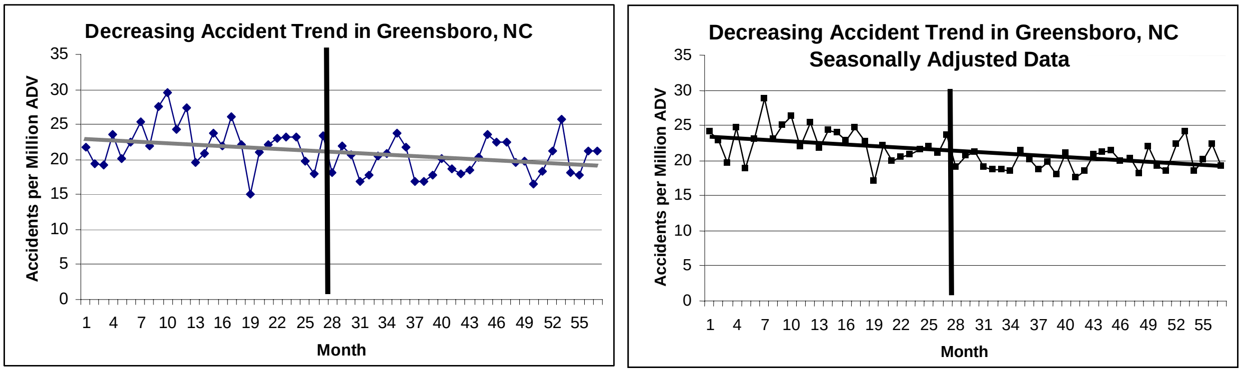
Even so, this simple approach is improper because it ignores other important information that might mask the true effects. For example, this approach ignores a possible time trend in accidents associated with unobserved factors (e.g., police enforcement intensity, roadway improvements, auto safety features, and precipitation levels). At a minimum, one must determine how the patterns of accidents are changing at *Non-RLC* sites (using them as *controls*). As a thought experiment, imagine two identical intersections, ***A*** and ***B***. Suppose that we place a red light camera at intersection ***B***, and accidents decrease by 10 percent. Should we conclude that the red light camera decreased accidents? Not necessarily, especially if accidents at intersection ***A*** also decreased by 10 percent. This points to a possible outside influence that is decreasing accident rates (e.g., the prevalence of antilock brakes on cars).

If accident rates at intersection ***A*** went down by 25 percent, then we might suspect that the red light camera is increasing the accident rate that would have occurred otherwise at ***B***. This becomes especially true if we see a similar comparison at many RLC sites and many control sites. In Table 4.3 we show the changes in accidents happening during the same period at the other 285 sites in the study. For total accidents and for each type (except Sideswipe) we see a decrease in accidents at the control sites as well. These decreases are also generally a larger percentage decrease than seen at the RLC sites. However, similar to the RLC sites, on a monthly basis we do see a small increase in angle crashes (56.62 to 58.04).

Table 4.3: Control Sites Not Chosen for RLC Installation												
	First 29 months of data						Last 28 months of data					
CRASH TYPE	FTL	AINJ	BINJ	CINJ	PDO	Total	FTL	AINJ	BINJ	CINJ	PDO	Total
REAR END, SLOW OR STOP	--	2	41	600	728	1371	--	2	42	570	663	1277
ANGLE	4	22	178	581	857	1642	4	12	168	609	832	1625
LEFT TURN, SAME ROADWAY	2	9	69	231	338	649	--	5	37	117	175	334
SIDESWIPE, SAME DIRECTION	--	--	8	33	211	252	--	--	4	30	235	269
LEFT TURN, DIFFERENT ROADWAYS	1	2	19	76	131	229	--	--	9	38	67	114
REAR END, TURN	--	--	1	22	35	58	--	--	5	18	23	46
TOTAL (including omitted categories)	10	46	406	1705	2660	4827	8	27	339	1538	2299	4211

Some may automatically credit the decrease in accidents at the control sites to the so-called "spillover effect". Evidence of a spillover effect must be shown by finding either a discrete drop or increasingly negative trend in accident rates after an RLC program begins. After testing for this break in the trend in many ways, we find no evidence that the pattern changed from the pre-RLC decreasing trend. In Figure 2, we display the accidents per million cars traveling through an intersection per day over the 57 months of the study. On the left are the actual data. On the right we clarify the trend by adjusting the rates for seasonal variations. In Greensboro we found generally lower accident rates in the winter and summer months, and higher rates in the spring and fall. In either graph, a discrete drop or shift in trend at the 27th month is not evident.[12] In fact, looking at the seasonally adjusted data, the trend appears to level off or even increase.

Figure 2: Accident Trend



4.1. *The Poisson Regression Model*

Given this background, a method to estimate the effect of red light cameras on accident rates, *ceteris paribus*, must control for as many possible confounding factors as possible. Following convention in analyzing count data, we use Poisson regression in this study. Because the dependent variables (y_i) in these equations are the counts of crashes by type and severity and are nonnegative, the distribution to use is Poisson, which is of the form:

$$P(y_i = k) = \frac{e^{-\lambda}\lambda^k}{k!} \qquad (1)$$

where $E(Y) = \lambda, Var(Y) = \lambda$, e is the base of the natural logarithm, λ is the expected value of the number of accidents, which in our model is determined by the characteristics of each intersection. To ensure that $E(y) = \lambda$ is positive, the functional form used is, $E(Y_i \mid X_i) = e^{BX_i}$ or $\ln(\lambda_i) = B_o + B_1X_1 + B_2X_2 + \ldots$. Following conventions in accident studies that use rates, i.e., accidents/volume, the left-hand side can be rewritten in logarithms as $\ln(\lambda_i / ADV_i) = B_o + B_1X_1 + B_2X_2 + \ldots$ Re-arranging the terms and solving gives,

$$\ln(\lambda_i) = B_o + B_1X_1 + B_2X_2 + \ldots + \ln(ADV_i) \qquad (2)$$

[12] We also checked for jumps and trend changes in the regression models which follow. In all cases, the continuous, linear trend pattern fit the data best.

Equation (2) implies that $\ln(ADV_i)$ could be included as an explanatory variable whose coefficient is constrained to one. However, as suggested in Maddala (1983, p. 52), including it as an unconstrained explanatory variable has merit. For example, if it is constrained to one, the obvious interpretation is that a 1 percent increase in volume must increase accident rates by exactly 1 percent. Freely estimating it allows for the possibility that doubling traffic volume may more or less than double accident rates. Indeed, it is known that some types of accidents are more likely to occur under conditions of lower traffic volume, such as when a driver falls asleep.

The model as described above is often called a Poisson regression model with a log link. In this model, the estimated coefficients (b_j) of the continuous variables are the proportional change in the monthly accident rate for small changes in X. For larger changes in X (say ΔX=1, as in a dummy variable), this is calculated as the proportional change in its expected value, which is $e^{b_j} - 1$, and the marginal effect on accidents per month of a change in x_i is,

$$\frac{\partial E(Y_i \mid x_i)}{\partial x_{i1}} = b_1 e^{b_o + b_1 x_{i1} + b_2 x_{i2} + \ldots} \qquad (3)$$

Where $b_o + b_1 x_{i1} + b_2 x_{i2} + \ldots$ is normally evaluated at the mean values of x_1, x_2, etc.

The b_j are estimated using a maximum likelihood technique. Of course, instead of the normal distribution, the Poisson distribution for count data is used. Rewriting equation (1) to include the parameters and explanatory variables,

$$P(Y_i = k \mid x_i) = \frac{e^{-e^{XB}} (e^{XB})^k}{k!} \qquad (4)$$

Taking the log, and substituting the observed y_i for k, we can write the log-likelihood function as

$$L(B) = \sum_{i=1}^{n} l_i B = \sum_{i=1}^{n} \{y_i x_i B - e^{X_i B}\} \qquad (5)$$

where we drop the last term ($-\log(y_i!)$) because it does not involve the B.

A major drawback of the Poisson regression is that the underlying probability distribution assumes that the mean and variance are equal. More often than not, this is a false assumption. When the variance is not equal to the mean, maximum likelihood estimates of the coefficients are unbiased; however, the standard errors will be inaccurate. If the variance is greater than the mean (over-dispersion), the reported standard errors will be biased downward and vice versa. One option is to simply adjust the standard errors using some estimate of the variance generated from the data. However, this method lowers the efficiency of the estimates. If over-dispersion is likely, the preferred method is to extend the Poisson model by adding an error term to Equation (2), which for mathematical convenience has a gamma distribution with a mean of one and variance α. This model is commonly called a Negative Binomial Model (Cameron and Trivedi, 1986). The interpretation of the Poisson and the negative binomial coefficients are the same. The only difference is the estimation of the α parameter, which is constrained to be greater than zero. The α is a measure of the degree to which the variance exceeds the mean of the distribution.

We attempted to run the Negative Binomial model, but they are notoriously hard to estimate. In many data sets, estimates cannot be computed for the coefficients. Because the Negative Binomial model failed to converge so often, we instead correct for possible overdispersion by using robust covariance estimators (Huber, 1967), which can help correct for these problems. The estimates were computed using Limdep version 8.0. Three goodness of fit measures are reported. The Chi squared test with 17 degrees of freedom tests for overall explanatory power of the model. The RsqP and RsqD are Pseudo R^2 measures that can be loosely interpreted at the "prediction accuracy" of the model. See Greene (2003, p. 742) for details on the calculation and interpretation. Note, however, that in count data models with low process means the prediction accuracy will almost always be very low.

4.2 Note on Correlation vs. Causation

Often in the results that follow, one will see results that seem counterintuitive at first. For example, it will often be the case that that longer all-red time is associated with increased accidents, and higher speed limits have negative relationships with total crashes. The counterintuitive results for all-red time and speed limits (and occasionally other variables) warrant special mention. Strictly speaking, none of the variables examined in this study were randomly assigned as in a true experimental setting. Indeed, most would argue that doing so would be irresponsible.

In this case, we see that longer all-red times are associated with intersections that have higher accident rates, ceteris paribus. A naïve interpretation would suggest that longer all-red times cause increased accidents. However, during the study, very few signal timings were changed, so in fact we know nothing about the impact of c*hanges* in red light timing. A more likely interpretation would be that engineers at the GDOT made some changes at dangerous intersections, such as prohibiting right turn on red, increasing all-red timing, and reducing speed limits at intersections. Because we do not observe many changes in these intersection characteristics, we cannot infer the effect of these changes in the data.

The only variables that may be (more or less) strictly interpreted as natural experiments are snowfall and precipitation amounts. To a lesser degree, the placement of red light cameras can be thought of as a natural experiment, keeping in mind probable regression to the mean biases (which tend to cause the RLC coefficient to be reported as a more negative number than the truth[13]). Of course, the major difference between the RLC variable and some of the others mentioned above is that we do include data on accident trends both before <u>and</u> after the installation of these cameras. We will, therefore, restrict our statements when discussing most of the explanatory variables to statements of association. Although we may use the word "cause" when discussing the estimated impacts of RLCs, it should be interpreted carefully. And, although not the optimal study design to determine actual cause and effect, we believe that our before-after design, controlling for as many other influences as possible, is the best practical method that can be used in such a study.

[13] Note that this bias makes it likely to find that red light cameras reduce accidents, even when they do not. As seen in the next section, it gives even more credence to the estimates showing an association of RLCs with increased accidents.

5. Estimation and Results: Crashes by Type

Individual equations for types and severity of accidents were estimated by maximum likelihood methods to determine the effects of red light cameras and other variables on type and severity of accidents at signalized intersections. Initial estimation showed that the equations for some types of crashes gave very poor results. These equations involved categories of accidents that were extremely rare, and so they were grouped together as described in the discussion of Table 3.1 (into 6 accident types and 3 severity levels).

As part of the estimation, we imposed three equality constraints involving six coefficients and three pairs of variables. These constraints were with respect to amber time for each road, all-red time, and one-way roads at intersections. Thus, for each pair of variables (e.g., all-red time for each road at an intersection), the estimated coefficients were set to be equal. The rationale for these constraints is that each pair of variables should have equal effects at intersections.

5.1. Total Crashes

Table 5.1 shows the estimated results for total crashes. The observed pattern follows the discussions in Section 4 quite well. The overall time trend (MONTH) is negative and highly significant. Since the coefficient -.004 is very close to zero, we can interpret this as roughly a 0.4 percent decrease in accidents over time. While this sounds small, this compounds to an almost 5 percent decrease on a yearly basis. Most of the coefficients have the expected signs, but as discussed in Section 4.2, the majority of the coefficients should not be interpreted literally.

The coefficient of RLCPRES is positive and highly statistically significant, indicating an increase in crash rates associated with the placement of a RLC. Because this coefficient is close to zero, the marginal effect should be calculated as $(e^{.349} - 1) \approx .42$, or a 42 percent increase. The model is estimating that, had an RLC not been placed at a particular intersection, we may have seen a 42% decrease in the accident rate at that intersection (if we could hold all other factors constant). Similar to what was seen in the raw data in Section 4, the sites with RLCs are not experiencing the decreasing trend in accidents seen elsewhere. Additionally, the other characteristics of intersections with RLCs are not explaining the difference in accident rates.

Three other coefficients from the regression are worthy of note. The weather variables SNOW and PRECIP are both statistically significant. The coefficient on SNOW is negative, implying that an additional inch of snow in a month is related to a 2 percent lower accident rate. Though this finding may appear counterintuitive, it reflects weather conditions in the study area. Greensboro receives very little snowfall, and when predicted, it is preceded by school and business closures that remove traffic from the roads. Thus, the reduction in traffic volume that occurs during snowfall is responsible for this relationship. The same result does not hold for total rainfall, which has a positive relationship with total crashes.

Finally, the natural logarithm of average daily volume Log(ADV) is interesting. As shown in Equation (2) in Section 4, this coefficient describes how accident counts relate to the volume of traffic at an intersection. A coefficient of 1.0 would imply that a 1 percent increase in volume would lead to a 1 percent increase in accidents. For the total number of accidents, we have an estimated coefficient of 1.23. This implies that overall, 1 percent more traffic is associated with more than a 1 percent increase in accidents. Of course, this will vary by the specific type of accident, as we shall see below.

Table 5.1: Total Crashes

Poisson Regression	
Dependent variable	Total Crashes
Weighting variable	None
Number of observations	17271
Log likelihood function	-17208.48
Restricted log likelihood	-19097.81
Chi squared	3778.670
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 20105.51591 RsqP= .1870	
G - squared = 18488.50363 RsqD= .1697	
Overdispersion tests: g=mu(i):	10.667
Overdispersion tests: g=mu(i)^2:	10.450
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-12.363	0.347	-35.621	0.000	
MONTH	-0.004	0.001	-5.304	0.000	29.000
RLCPRES	0.349	0.046	7.649	0.000	0.029
TOTLTL	0.079	0.015	5.135	0.000	1.640
DEDRTL	0.046	0.023	2.004	0.045	0.446
SWLK	0.124	0.027	4.493	0.000	0.432
SLDMED	-0.074	0.030	-2.478	0.013	0.175
PEDSIG	-0.250	0.032	-7.846	0.000	0.257
NLT	0.036	0.036	1.003	0.316	0.102
NTR	0.101	0.026	3.912	0.000	0.208
SNOW	-0.020	0.008	-2.542	0.011	0.410
PRECIP	0.009	0.005	1.790	0.074	3.645
TOTLN	0.003	0.005	0.619	0.536	8.135
ST1FLOW	-0.112	0.024	-4.640	0.000	0.911
ST2FLOW	-0.112	0.024	-4.640	0.000	0.861
ST1RED	0.010	0.013	0.774	0.439	1.552
ST2RED	0.010	0.013	0.774	0.439	1.543
AMBD1	-0.133	0.028	-4.738	0.000	0.569
AMBD2	-0.133	0.028	-4.738	0.000	0.567
ST1SP	-0.008	0.002	-3.499	0.001	34.670
ST2SP	-0.008	0.002	-3.499	0.001	34.868
Log(ADV)	1.233	0.031	40.399	0.000	10.134

Notes: Month = time trend, RLCPRES = presence of RLC, TOTLTL = number of left turn lanes at intersection, DEDRTL = dedicated right turn lane at intersection (yes = 1, no =0), SWLK = sidewalk at intersection (yes = 1, no = 0), SLDMED = solid median at intersection, PEDSIG = pedestrian signal, NLT and NTR = no left turn and no right turn on red signs, ST#Flow = traffic on road 1 or 2 (one-way road = 0, two-way road = 1), ST#RED = all red time on road 1 or 2, AMBD# = amber time above recommended time on road 1 or 2, ST#SP = posted speed limit on roads 1 or 2, LOG(ADV) = natural log of daily traffic volume.

5.2. Angle Crashes

Given the results above, it is of interest to examine how various types of crashes at signalized intersections are related to red light cameras, controlling for the effects of road and traffic light characteristics, traffic signs, and weather. The first type of crash considered is angle or front-into-side crashes. The results from analyzing angle crashes are in Table 5.2. Consistent with our earlier finding, the coefficient of red light cameras is positive; however, the p value 0.183 is too high to confidently say that this coefficient is nonzero. This is consistent with the information in Tables 4.2 and 4.3, where small increases were seen in the monthly angle accident rate at both RLC and NON-RLC sites. The small, positive coefficient on MONTH is also consistent with the raw data.

As mentioned previously, this category of accidents is the one most often cited as the target of RLC programs. If RLCs reduce the number of violators who enter into an intersection *well after the signal has turned red*, then we would expect the angle accidents to decrease. While we cannot confidently say that angle accidents at RLC sites are increasing relative to other sites, there is certainly no evidence of a decrease. In fact, the p value of a one tailed test ($H_o : B \leq 0, H_a : B > 0$) would be 0.0915. The fact that this category of accident is going up over time does not indicate that an overall benefit is being felt from reduced red light running at other intersections due to a “spillover effect.”

Looking at the other variables, these accidents are positively related to the number of left turn lanes, dedicated right turn lanes, and presence of sidewalks. These factors are all indicators of a wider carriageway that vehicles must cross before they clear an intersection. Again, these relationships are not causal, merely correlations. We also see that one way roads, intersections with pedestrian signals, and longer than the minimum recommended amber timing are associated with decreased accidents. Finally, the Coefficient on Log(ADV) is extremely close to one, indicating that an increase in traffic volume is associated with an equal percentage increase in these angle accidents.

Table 5.2: Angle Crashes

Poisson Regression	
Dependent variable	ANGLE
Weighting variable	None
Number of observations	17271
Log likelihood function	-9411.363
Restricted log likelihood	-9856.574
Chi squared	890.4210
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 18536.82668 RsqP= .0471	
G - squared = 12163.52994 RsqD= .0682	
Overdispersion tests: g=mu(i): 5.777	
Overdispersion tests: g=mu(i)^2: 4.930	
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-10.793	0.544	-19.834	0.000	
MONTH	0.003	0.001	2.593	0.010	29.000
RLCPRES	0.111	0.084	1.332	0.183	0.029
TOTLTL	0.084	0.025	3.400	0.001	1.640
DEDRTL	0.074	0.037	2.031	0.042	0.446
SWLK	0.330	0.043	7.728	0.000	0.432
SLDMED	-0.080	0.050	-1.597	0.110	0.175
PEDSIG	-0.364	0.051	-7.212	0.000	0.257
NLT	0.055	0.057	0.960	0.337	0.102
NTR	0.104	0.041	2.544	0.011	0.208
SNOW	-0.015	0.012	-1.218	0.223	0.410
PRECIP	-0.002	0.008	-0.240	0.810	3.645
TOTLN	-0.009	0.009	-0.951	0.342	8.135
ST1FLOW	-0.228	0.037	-6.096	0.000	0.911
ST2FLOW	-0.228	0.037	-6.096	0.000	0.861
ST1RED	-0.025	0.020	-1.244	0.213	1.552
ST2RED	-0.025	0.020	-1.244	0.213	1.543
AMBD1	-0.233	0.046	-5.039	0.000	0.569
AMBD2	-0.233	0.046	-5.039	0.000	0.567
ST1SP	-0.011	0.004	-2.865	0.004	34.670
ST2SP	-0.011	0.004	-2.865	0.004	34.868
Log(ADV)	1.030	0.047	22.125	0.000	10.134

Notes: Month = time trend, RLCPRES = presence of RLC, TOTLTL = number of left turn lanes at intersection, DEDRTL = dedicated right turn lane at intersection (yes = 1, no =0), SWLK = sidewalk at intersection (yes = 1, no = 0), SLDMED = solid median at intersection, PEDSIG = pedestrian signal, NLT and NTR = no left turn and no right turn on red signs, ST#Flow = traffic on road 1 or 2 (one-way road = 0, two-way road = 1), ST#RED = all red time on road 1 or 2, AMBD# = amber time above recommended time on road 1 or 2, ST#SP = posted speed limit on roads 1 or 2, LOG(ADV) = natural log of daily traffic volume.

5.3. Crashing into the Rear of a Slowed or Stopped Vehicle

As mentioned previously, this category of crashes is likely to suffer from censoring due to the $1,000/injury reporting threshold. Table 5.3 shows the average damage per vehicle involved for the various crash types. Note that the lowest two categories for vehicle damage correspond to pedestrians and cyclists and are likely to be reported under the injury threshold.

Table 5.4 shows the estimation results for accidents that occur when a moving vehicle crashes into the rear of a slowed or stopped vehicle at an intersection. We expected this type of accident to increase because drivers may panic from seeing the camera and stop prematurely. As can be expected, with rear-end accidents increasing at RLC sites but decreasing elsewhere (see Tables 4.2 and 4.3), the model estimates a very large impact of RLCs on rear-end crashes. The coefficient of 0.578 yields a marginal effect of an approximate 78 percent increase in the accident risk associated with these sites. While this sounds unbelievably high, one can simplistically understand this estimate in the following way: Similar to the overall time trend for Total Crashes, for Rear End, Slow or Stopped the prevailing time trend is a decrease of 0.4 percent per month, or around 5 percent per year. Over the course of the study this could account for an approximate 25 percent decrease. However, in the before/after table (Table 4.2), the raw data show approximately a 10 percent *increase* at the RLC sites. This difference alone accounts for roughly a 35 percent difference attributable to the RLC placement.

Additionally, we see that snow is associated with a decrease in monthly rear-end crashes due to its regional impact on traffic volumes. We also see that total precipitation has an increasing relationship with rear-end crashes, which would be expected with the decreased traction in wet weather. The coefficient on Log(ADV) of 1.831 tells us that intersections with high traffic volume are likely to experience substantially more rear-end crashes, even after taking volume into account.

Interestingly, we also see that more rear-end accidents occur on one-way streets, where speed limits are higher, and where the amber timing is longer than recommended. We could conjecture that when there is a long amber time, drivers who are aware of the long time may be caught off guard by unaware drivers stopping unexpectedly.

Crash Type	Mean Damage/Vehicle
PEDESTRIAN	$128.75
PEDALCYCLIST	$601.76
BACKING UP	$1,094.28
OTHER NON-COLLISION	$1,436.49
SIDESWIPE, SAME DIRECTION	$1,493.12
REAR END, TURN	$1,513.32
REAR END, SLOW OR STOP	$1,588.78
ANIMAL	$1,681.58
RIGHT TURN, SAME ROADWAY	$1,778.07
RIGHT TURN, DIFFERENT ROADWAYS	$1,867.83
PARKED MOTOR VEHICLE	$2,052.70
UNKNOWN	$2,286.84
SIDESWIPE,OPPOSITE DIRECTION	$2,480.12
MOVABLE OBJECT	$2,500.00
LEFT TURN, DIFFERENT ROADWAYS	$2,546.25
RAN OFF ROAD - STRAIGHT	$2,626.91
LEFT TURN, SAME ROADWAY	$2,666.82
RAN OFF ROAD - LEFT	$2,824.24
ANGLE	$2,915.99
OTHER COLLISION WITH VEHICLE	$3,163.95
RAN OFF ROAD - RIGHT	$3,405.96
HEAD ON	$3,433.50
FIXED OBJECT	$3,564.58
OVERTURN/ROLLOVER	$4,187.50

Table 5.4: Crashing into rear of slowed or stopped vehicles

Poisson Regression	
Dependent variable	REARSTOP
Weighting variable	None
Number of observations	17271
Log likelihood function	-8064.160
Restricted log likelihood	-9455.494
Chi squared	2782.668
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 19046.08965 RsqP= .1705	
G - squared = 10319.68886 RsqD= .2124	
Overdispersion tests: g=mu(i): 4.020	
Overdispersion tests: g=mu(i)^2: 3.612	
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-21.683	0.627	-34.571	0.000	
MONTH	-0.004	0.001	-2.943	0.003	29.000
RLCPRES	0.578	0.065	8.906	0.000	0.029
TOTLTL	0.063	0.027	2.299	0.022	1.640
DEDRTL	-0.008	0.040	-0.193	0.847	0.446
SWLK	-0.072	0.051	-1.411	0.158	0.432
SLDMED	-0.086	0.048	-1.797	0.072	0.175
PEDSIG	-0.057	0.057	-1.005	0.315	0.257
NLT	0.101	0.060	1.688	0.091	0.102
NTR	0.121	0.044	2.764	0.006	0.208
SNOW	-0.036	0.013	-2.672	0.008	0.410
PRECIP	0.015	0.008	1.779	0.075	3.645
TOTLN	0.005	0.009	0.598	0.550	8.135
ST1FLOW	0.198	0.053	3.727	0.000	0.911
ST2FLOW	0.198	0.053	3.727	0.000	0.861
ST1RED	0.010	0.021	0.459	0.646	1.552
ST2RED	0.010	0.021	0.459	0.646	1.543
AMBD1	0.094	0.044	2.132	0.033	0.569
AMBD2	0.094	0.044	2.132	0.033	0.567
ST1SP	0.007	0.004	1.971	0.049	34.670
ST2SP	0.007	0.004	1.971	0.049	34.868
Log(ADV)	1.831	0.058	31.698	0.000	10.134

Notes: Month = time trend, RLCPRES = presence of RLC, TOTLTL = number of left turn lanes at intersection, DEDRTL = dedicated right turn lane at intersection (yes = 1, no =0), SWLK = sidewalk at intersection (yes = 1, no = 0), SLDMED = solid median at intersection, PEDSIG = pedestrian signal, NLT and NTR = no left turn and no right turn on red signs, ST#Flow = traffic on road 1 or 2 (one-way road = 0, two-way road = 1), ST#RED = all red time on road 1 or 2, AMBD# = amber time above recommended time on road 1 or 2, ST#SP = posted speed limit on roads 1 or 2, LOG(ADV) = natural log of daily traffic volume.

5.4. Left Turning Vehicles on Different Roadways

Another type of accident studied involved a vehicle turning left crashing with a car traveling on a different roadway. Table 5.5 shows the results of the negative binomial regression. The regression results show that this type of accident reduced over the analysis period as evidenced by the negative (-0.028) and statistically significant (probability < 0.0001) coefficient of MONTH in the results. However, this type of accident reduced even more at the RLC sites after the introduction of the RLC.

This reduction in accidents among left turning vehicles and different roadways is the one example of a benefit found related to the red light cameras. The negative coefficient of -0.922 has a p value of .052, almost statistically significant at the .05 level. The estimated effect is large, suggesting a 60 percent decrease of this type of crash. However, the estimate is not very precise and could greatly over- or underestimate the true impact. Though this is one of the more common types of accidents, it is far less common than angle or rear-end accidents, representing approximately 3.57 percent of the accidents in this study. Therefore, this large percentage decrease should be judged in the context that there were only 40 of these accidents during the approximately five years of the study at the RLC sites.

Nevertheless, it is striking to see such a decrease, from 34 accidents in the "before" period, to only 6 after. Perhaps this information could be used to discover an intervention that has a similar impact on these left turning crashes that does not possess the negative effects on other types of crashes.

5.5. Sideswipe a Vehicle Moving in the Same Direction

Another traffic accident that occurs at or near intersections is a vehicle side swiping another moving in the same direction. This type of accident is also likely to be highly censored due to the low damage value of these crashes and the unlikelihood of injury. This type of accident may occur due to distraction or an attempt to change lanes without looking for vehicles in blind spots. Table 5.6 shows the estimated parameters for this type of accident and their levels of significance. From these results, this type of accident increased in the analysis period. However, the addition of a RLC to an intersection is associated with a further increase. Precipitation appeared to be unrelated to this type of accident. The high (1.416) coefficient on Log(ADV) suggests that roads with high volumes experience this type of accident much more frequently, so that an intersection with twice the volume will experience much more than twice the number of sideswipes.

Table 5.5: Crashes involving left turning vehicles on different roadways

Poisson Regression	
Dependent variable	LTURNDIF
Weighting variable	None
Number of observations	17271
Log likelihood function	-1735.354
Restricted log likelihood	-1857.693
Chi squared	244.6795
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 18216.62437 RsqP= .0393	
G - squared = 2736.59185 RsqD= .0821	
Overdispersion tests: g=mu(i):	2.562
Overdispersion tests: g=mu(i)^2:	4.017
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-13.009	1.732	-7.510	0.000	
MONTH	-0.028	0.004	-7.063	0.000	29.000
RLCPRES	-0.922	0.475	-1.941	0.052	0.029
TOTLTL	0.154	0.074	2.080	0.038	1.640
DEDRTL	0.072	0.113	0.641	0.522	0.446
SWLK	-0.201	0.157	-1.280	0.201	0.432
SLDMED	0.028	0.149	0.187	0.852	0.175
PEDSIG	-0.202	0.181	-1.113	0.266	0.257
NLT	0.274	0.194	1.412	0.158	0.102
NTR	-0.546	0.159	-3.429	0.001	0.208
SNOW	0.038	0.041	0.939	0.348	0.410
PRECIP	0.042	0.024	1.703	0.089	3.645
TOTLN	0.004	0.030	0.135	0.893	8.135
ST1FLOW	0.424	0.172	2.464	0.014	0.911
ST2FLOW	0.424	0.172	2.464	0.014	0.861
ST1RED	0.034	0.051	0.671	0.502	1.552
ST2RED	0.034	0.051	0.671	0.502	1.543
AMBD1	-0.309	0.138	-2.232	0.026	0.569
AMBD2	-0.309	0.138	-2.232	0.026	0.567
ST1SP	-0.014	0.013	-1.099	0.272	34.670
ST2SP	-0.014	0.013	-1.099	0.272	34.868
Log(ADV)	0.975	0.150	6.505	0.000	10.134

Notes: Month = time trend, RLCPRES = presence of RLC, TOTLTL = number of left turn lanes at intersection, DEDRTL = dedicated right turn lane at intersection (yes = 1, no =0), SWLK = sidewalk at intersection (yes = 1, no = 0), SLDMED = solid median at intersection, PEDSIG = pedestrian signal, NLT and NTR = no left turn and no right turn on red signs, ST#Flow = traffic on road 1 or 2 (one-way road = 0, two-way road = 1), ST#RED = all red time on road 1 or 2, AMBD# = amber time above recommended time on road 1 or 2, ST#SP = posted speed limit on roads 1 or 2, LOG(ADV) = natural log of daily traffic volume.

Table 5.6: Sideswiped accidents: Same direction

Poisson Regression	
Dependent variable	SSWSAM
Weighting variable	None
Number of observations	17271
Log likelihood function	-2523.097
Restricted log likelihood	-2687.213
Chi squared	328.2319
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 17115.88469 RsqP= .0246	
G - squared = 3832.37488 RsqD= .0789	
Overdispersion tests: g=mu(i): -.984	
Overdispersion tests: g=mu(i)^2: -.556	
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-15.126	1.323	-11.437	0.000	
MONTH	0.005	0.003	1.750	0.080	29.000
RLCPRES	0.352	0.165	2.132	0.033	0.029
TOTLTL	0.093	0.057	1.627	0.104	1.640
DEDRTL	0.039	0.086	0.449	0.653	0.446
SWLK	0.205	0.100	2.050	0.040	0.432
SLDMED	0.088	0.105	0.832	0.406	0.175
PEDSIG	-0.269	0.116	-2.317	0.021	0.257
NLT	-0.116	0.139	-0.834	0.404	0.102
NTR	0.024	0.102	0.237	0.813	0.208
SNOW	-0.067	0.032	-2.091	0.037	0.410
PRECIP	-0.021	0.019	-1.074	0.283	3.645
TOTLN	0.035	0.020	1.721	0.085	8.135
ST1FLOW	-0.569	0.079	-7.218	0.000	0.911
ST2FLOW	-0.569	0.079	-7.218	0.000	0.861
ST1RED	0.168	0.046	3.649	0.000	1.552
ST2RED	0.168	0.046	3.649	0.000	1.543
AMBD1	-0.342	0.100	-3.418	0.001	0.569
AMBD2	-0.342	0.100	-3.418	0.001	0.567
ST1SP	-0.036	0.008	-4.324	0.000	34.670
ST2SP	-0.036	0.008	-4.324	0.000	34.868
Log(ADV)	1.416	0.122	11.611	0.000	10.134

Notes: Month = time trend, RLCPRES = presence of RLC, TOTLTL = number of left turn lanes at intersection, DEDRTL = dedicated right turn lane at intersection (yes = 1, no =0), SWLK = sidewalk at intersection (yes = 1, no = 0), SLDMED = solid median at intersection, PEDSIG = pedestrian signal, NLT and NTR = no left turn and no right turn on red signs, ST#Flow = traffic on road 1 or 2 (one-way road = 0, two-way road = 1), ST#RED = all red time on road 1 or 2, AMBD# = amber time above recommended time on road 1 or 2, ST#SP = posted speed limit on roads 1 or 2, LOG(ADV) = natural log of daily traffic volume.

5.6. Accidents Involving Left Turning Vehicles on the Same Roadway

Table 5.7 shows that over time, accidents involving left-turning vehicles on the same roadway have reduced by a large percentage, as shown by the time coefficient of –0.024 (probability < 0.0001). In addition, several other factors seem to be associated with lower levels of these accidents, including pedestrian crossing signals, longer amber time, and higher posted speed limits. The absence of a red light camera has a weak, positive relationship with these accidents. Specifically, its coefficient is positive (0.279) and marginally statistically significant ($p = 0.078$). All-red time, the number of left-turn lanes, and the presence of dedicated right-turn lanes are positively associated with this type of accident.

As could be expected, if one of the carriageways does not allow left turns (NLT), this will cause a large decrease in accidents involving left turns, though this observation probably has little policy relevance. However, the effect of amber time is quite large and should be investigated in a more experimental setting.

5.7. Other Crashes

All other types of crashes were analyzed in aggregate form because each occurred very rarely. Because of the extremely varied nature of these other accidents, it is more difficult to interpret the meaning of the coefficients. However, in Table 5.8 the pattern of sign and significance is largely similar to the results seen in the other categories of crashes, with a prevailing negative time trend and a positive effect associated with red light cameras. However, the p value of 0.113 is not low enough to confidently conclude that a relationship exists with the presence of red light cameras.

Table 5.7: Left turn in same direction

Poisson Regression	
Dependent variable	LTURNSAM
Weighting variable	None
Number of observations	17271
Log likelihood function	-3992.030
Restricted log likelihood	-4229.833
Chi squared	475.6053
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 18405.98517 RsqP= .0349	
G - squared = 5874.86471 RsqD= .0749	
Overdispersion tests: g=mu(i):	2.932
Overdispersion tests: g=mu(i)^2:	2.980
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-10.234	1.018	-10.057	0.000	
MONTH	-0.024	0.002	-11.095	0.000	29.000
RLCPRES	0.279	0.158	1.762	0.078	0.029
TOTLTL	0.103	0.042	2.427	0.015	1.640
DEDRTL	0.195	0.066	2.933	0.003	0.446
SWLK	0.203	0.079	2.568	0.010	0.432
SLDMED	-0.207	0.090	-2.295	0.022	0.175
PEDSIG	-0.441	0.092	-4.769	0.000	0.257
NLT	-0.357	0.128	-2.784	0.005	0.102
NTR	0.101	0.077	1.307	0.191	0.208
SNOW	0.027	0.024	1.150	0.250	0.410
PRECIP	-0.002	0.015	-0.148	0.883	3.645
TOTLN	0.007	0.015	0.491	0.624	8.135
ST1FLOW	-0.179	0.069	-2.582	0.010	0.911
ST2FLOW	-0.179	0.069	-2.582	0.010	0.861
ST1RED	0.025	0.033	0.755	0.450	1.552
ST2RED	0.025	0.033	0.755	0.450	1.543
AMBD1	-0.387	0.093	-4.166	0.000	0.569
AMBD2	-0.387	0.093	-4.166	0.000	0.567
ST1SP	-0.028	0.008	-3.531	0.000	34.670
ST2SP	-0.028	0.008	-3.531	0.000	34.868
Log(ADV)	1.018	0.088	11.615	0.000	10.134

Notes: Month = time trend, RLCPRES = presence of RLC, TOTLTL = number of left turn lanes at intersection, DEDRTL = dedicated right turn lane at intersection (yes = 1, no =0), SWLK = sidewalk at intersection (yes = 1, no = 0), SLDMED = solid median at intersection, PEDSIG = pedestrian signal, NLT and NTR = no left turn and no right turn on red signs, ST#Flow = traffic on road 1 or 2 (one-way road = 0, two-way road = 1), ST#RED = all red time on road 1 or 2, AMBD# = amber time above recommended time on road 1 or 2, ST#SP = posted speed limit on roads 1 or 2, LOG(ADV) = natural log of daily traffic volume.

Table 5.8: Other accidents

Poisson Regression	
Dependent variable	OTHACC
Weighting variable	None
Number of observations	17271
Log likelihood function	-5103.704
Restricted log likelihood	-5207.737
Chi squared	208.0663
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 17758.85244 RsqP = .0123	
G - squared = 7351.35199 RsqD = .0275	
Overdispersion tests: g=mu(i):	2.057
Overdispersion tests: g=mu(i)^2:	2.055
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-8.509	0.846	-10.055	0.000	
MONTH	-0.003	0.002	-1.675	0.094	29.000
RLCPRES	0.196	0.124	1.584	0.113	0.029
TOTLTL	0.099	0.038	2.595	0.010	1.640
DEDRTL	-0.002	0.057	-0.032	0.975	0.446
SWLK	-0.003	0.070	-0.038	0.970	0.432
SLDMED	-0.114	0.074	-1.548	0.122	0.175
PEDSIG	-0.146	0.077	-1.895	0.058	0.257
NLT	0.067	0.091	0.741	0.459	0.102
NTR	0.143	0.066	2.183	0.029	0.208
SNOW	-0.023	0.019	-1.228	0.219	0.410
PRECIP	0.018	0.012	1.449	0.147	3.645
TOTLN	0.014	0.013	1.067	0.286	8.135
ST1FLOW	0.021	0.063	0.329	0.742	0.911
ST2FLOW	0.021	0.063	0.329	0.742	0.861
ST1RED	-0.001	0.030	-0.035	0.972	1.552
ST2RED	-0.001	0.030	-0.035	0.972	1.543
AMBD1	-0.119	0.076	-1.576	0.115	0.569
AMBD2	-0.119	0.076	-1.576	0.115	0.567
ST1SP	-0.012	0.006	-1.934	0.053	34.670
ST2SP	-0.012	0.006	-1.934	0.053	34.868
Log(ADV)	0.661	0.071	9.324	0.000	10.134

Notes: Month = time trend, RLCPRES = presence of RLC, TOTLTL = number of left turn lanes at intersection, DEDRTL = dedicated right turn lane at intersection (yes = 1, no =0), SWLK = sidewalk at intersection (yes = 1, no = 0), SLDMED = solid median at intersection, PEDSIG = pedestrian signal, NLT and NTR = no left turn and no right turn on red signs, ST#Flow = traffic on road 1 or 2 (one-way road = 0, two-way road = 1), ST#RED = all red time on road 1 or 2, AMBD# = amber time above recommended time on road 1 or 2, ST#SP = posted speed limit on roads 1 or 2, LOG(ADV) = natural log of daily traffic volume.

6. Estimation and Results: Crashes by Severity

Given that red light cameras are associated with increases in most types of accidents, there is the possibility that RLC benefits are found in a reduction in the severity of accidents. As noted earlier, severity of crashes is broken into the following categories: fatalities, severe, evident/visible, possible, and property damage. Again, accident reports are filed only for accidents where the officer estimates property damage of $1,000 or more, so the property damage data are censored. The three most severe categories of crashes are very small percentages of total crashes individually, and are, therefore, combined in the analysis following into a category called "Severe" crashes. For the convenience of the reader, we duplicate Table 2.1 showing the various levels of severity and their estimated costs:

Table 2.1: Comprehensive Costs, Each Occurrence (KABC Scale)

Severity	Description	FHWA (1994)	FHWA (2002)	NCDOT 2001
K (FTL)	Fatal	$2,600,000	$2,979,600	$3,300,000
A	Incapacitating	180,000	206,280	200,000
B	Evident	36,000	41,256	57,000
C	Possible	19,000	21,774	27,000
PDO	Property Damage Only	2,000	2,292	3,900

In the previous section, we found that RLCs are associated with an overall increase in the number of accidents at an intersection. If RLCs provide a benefit in terms of reduction in severity, then we ought to see that when a RLC is placed at an intersection, Severe accidents decrease, and type C (possible) and Property Damage Only (PDO) crashes increase.

Before we present the results of the regression analysis, let us take a look once again at Tables 4.2 and 4.3. The raw data show that at RLC sites: fatalities go from 0 to 1, A injuries go from 6 to 5, and B injuries decrease impressively. There is little change in C injuries or PDO accidents between the two periods.

At the control sites, Table 4.3 shows that those intersections not involved with the RLC program saw a drop in fatalities from 10 to 8, an impressive drop in A injuries from 46 to 27, a substantial drop in B injuries (406 to 339), and moderate decreases in both C injuries and PDO crashes. With the exception of the B injuries, the intersections that were not part of the RLC program appear to be faring much better in terms of accident reduction. These patterns are similar to those seen with all types of accidents both county- and statewide. Table 6.1 shows the overall severity pattern for all accidents occurring in Guilford County, North Caroina, from 1998 through 2002.[14] We also show the pattern from the neighboring county of Forsyth for comparison, because it is of similar size and has not participated in a RLC program.

[14] Complete data for the year 2003 is not at this time this report was printing

Table 6.1: NC County Accident Trends										
Guilford County (Contains Greensboro) (Pop.: 424,000)										
Category	1998		1999		2000		2001		2002	
	Crashes	Injuries	Crashes	Injuries	Crashes	Injuries	Crashes	Injuries	Crashes	Injuries
Fatal	60	**69**	46	**49**	56	**58**	55	**61**	45	**48**
Non Fatal Injury	6,124	**10,082**	6,237	**10,074**	5,811	**9,247**	5,811	**9,083**	5,607	**8,802**
PDO	7,291		7,841		8,076		8,071		7,763	
Total	13,475	**10,151**	14,124	**10,123**	13,943	**9,305**	13,937	**9,144**	13,415	**8,850**
Forsyth County (Pop.: 310,000)										
Fatal	34	**39**	32	**35**	39	**43**	28	**29**	40	**43**
Non Fatal Injury	3,266	**5,120**	3,121	**4,872**	2,947	**4,608**	3,054	**4,639**	2,958	**4,568**
PDO	4,145		4,389		5,210		5,422		5,374	
Total	7,445	**5,159**	7,542	**4,907**	8,196	**4,651**	8,504	**4,668**	8,372	**4,611**

From http://www.doh.dot.state.nc.us/preconstruct/traffic/Safety/ses/profiles/CountyProfiles.pdf

If we apply the NCDOT's cost estimates in Table 2.1 to the data on crash severity in tables 4.2 and 4.3, the non-RLC sites saw a decrease in crash costs of 16.5 percent, whereas the RLC sites experienced an increase in crash costs of 4.9 percent over the same period. If we ignore the one fatality that occurred at the RLC sites during the after period, then the RLC sites would experience a decrease in costs of 16.2 percent. The reliable estimation of the risk of rare events such as fatal crashes at intersections is extremely difficult, yet should not be disregarded entirely.

In the next section, we turn to the regression analysis to see what relationship is found between the placement of a RLC and the accident risk when the effects of weather, traffic volume, and intersection characteristics are controlled for.

6.1. Severe Crashes

Table 6.2 shows the Poisson regression results for severe crashes. Similar to what the raw data showed us, the negative coefficient for MONTH describes an overall decreasing trend in severe accidents. This overall trend is likely in part due the increased use of airbags, child safety seats, crumple zones, and the like. The coefficient on RLCPRES is positive; however, the p value indicates that this positive estimate is neither large enough nor reliable enough to conclude that adding a red light camera is associated with an increase in severe accidents. However, it does contradict the hypothesis that RLCs produce a benefit by reducing the severity of accidents relative to other intersections.

Another factor positively related to severe crashes is precipitation. For these severe crashes, there is a roughly one-to-one relationship with traffic volume (coefficient = .970).

Table 6.2: Severe crashes

Poisson Regression	
Dependent variable	SEVERE
Weighting variable	None
Number of observations	17271
Log likelihood function	-3657.914
Restricted log likelihood	-3779.015
Chi squared	242.2018
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 17542.73309 RsqP=	.0109
G - squared = 5438.12995 RsqD=	.0426
Overdispersion tests: g=mu(i):	1.019
Overdispersion tests: g=mu(i)^2:	.827
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-12.123	1.041	-11.647	0.000	
MONTH	-0.008	0.002	-3.759	0.000	29.000
RLCPRES	0.091	0.162	0.563	0.573	0.029
TOTLTL	0.069	0.047	1.465	0.143	1.640
DEDRTL	0.131	0.071	1.846	0.065	0.446
SWLK	0.109	0.086	1.265	0.206	0.432
SLDMED	0.022	0.090	0.241	0.810	0.175
PEDSIG	-0.286	0.097	-2.953	0.003	0.257
NLT	0.046	0.108	0.424	0.671	0.102
NTR	0.218	0.075	2.898	0.004	0.208
SNOW	-0.010	0.025	-0.395	0.693	0.410
PRECIP	0.026	0.016	1.690	0.091	3.645
TOTLN	0.011	0.016	0.699	0.485	8.135
ST1FLOW	-0.142	0.073	-1.937	0.053	0.911
ST2FLOW	-0.142	0.073	-1.937	0.053	0.861
ST1RED	-0.029	0.038	-0.765	0.444	1.552
ST2RED	-0.029	0.038	-0.765	0.444	1.543
AMBD1	-0.058	0.090	-0.644	0.520	0.569
AMBD2	-0.058	0.090	-0.644	0.520	0.567
ST1SP	-0.007	0.008	-0.878	0.380	34.670
ST2SP	-0.007	0.008	-0.878	0.380	34.868
Log(ADV)	0.970	0.088	11.067	0.000	10.134

Note: RLC = Red light camera present (yes =1, no = 0), NTR = No turn on right, NLT = No left turn, LTA = Left turn allowed, DEDRTL = Dedicated right turn lane (yes = 1, No = 0), SWLK = Sidewalk (yes = 1, no = 0), PEDSIG = pedestrian signal (yes =1, no = 0), ST1FLOW =one-way traffic on road 1 (yes = 1, no = 0), ST2FLOW = one way road on road 2 (yes = 1, no = 0), ST1RED = All red time on road 1, ST2RED = All red time on road 2, ST1AMB = amber time on road 1, ST2AMB = Amber time on road 2, ADT = Average annual daily traffic volume.

6.2. Crashes Resulting in Possible Injury

Besides severe crashes, those that police reports record as having caused possible injuries were also analyzed and their results are in Table 6.3. Here also, this type of crash has been decreasing over time, but we estimate a large (0.406), highly statistically significant ($p<0.001$) increase associated with the presence of a RLC. The coefficient on traffic volume is larger than 1.0, implying that higher volume roads will have many more C type accidents. We again see that snowfall decreases this type of accidents; however, the p value for precipitation is a bit too high (0.181) to be certain of an impact.

6.3. Crashes Involving Property Damage

Table 6.4 shows the results of crashes resulting in property damage. The overall pattern is very similar to what is seen with possible injury crashes. These crashes have also been decreasing over time as indicated by the negative (-0.004) and statistically significant ($p<0.001$) coefficient of time. However, we once again see that the addition of a RLC to an intersection is associated with an increase in these accidents relative to what is happening at other sites.

Pedestrian-crossing signals, longer amber times, and higher posted traffic-speed limits also are negatively related to crashes resulting in property damage. While pedestrian-crossing signals may allow drivers to exercise caution at intersections and reduce crashes, longer amber times, as noted previously, allow vehicles to proceed safely through intersections.

Contrary to these findings are those variables in the table whose coefficients are positive and statistically significant; therefore, suggesting they are *associated with* an increase accidents that result in property damage. Notable among them are the total number of left turn lanes, dedicated right turn lanes, no left turn, and sidewalks. However, it is worth repeating once more that these are merely associations because there was very little intra-site variation in these intersection characteristics (aside from adding RLCs); we cannot say what would happen if these variables were changed. They describe what is seen, not what would be seen at intersections should one of these particular variables change.

Table 6.3: Crashes resulting in possible injury

Poisson Regression	
Dependent variable	CINJ
Weighting variable	None
Number of observations	17271
Log likelihood function	-9375.463
Restricted log likelihood	-10118.50
Chi squared	1486.078
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 18504.36387 RsqP=	.0949
G - squared = 11987.31206 RsqD=	.1103
Overdispersion tests: g=mu(i):	4.738
Overdispersion tests: g=mu(i)^2:	4.788
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-13.676	0.558	-24.503	0.000	
MONTH	-0.003	0.001	-2.713	0.007	29.000
RLCPRES	0.406	0.073	5.559	0.000	0.029
TOTLTL	0.076	0.024	3.220	0.001	1.640
DEDRTL	0.011	0.037	0.307	0.759	0.446
SWLK	0.144	0.044	3.266	0.001	0.432
SLDMED	-0.098	0.048	-2.034	0.042	0.175
PEDSIG	-0.374	0.052	-7.172	0.000	0.257
NLT	-0.037	0.058	-0.628	0.530	0.102
NTR	0.158	0.041	3.861	0.000	0.208
SNOW	-0.041	0.013	-3.220	0.001	0.410
PRECIP	0.011	0.008	1.338	0.181	3.645
TOTLN	0.002	0.009	0.187	0.852	8.135
ST1FLOW	-0.038	0.041	-0.928	0.353	0.911
ST2FLOW	-0.038	0.041	-0.928	0.353	0.861
ST1RED	0.042	0.020	2.163	0.031	1.552
ST2RED	0.042	0.020	2.163	0.031	1.543
AMBD1	-0.163	0.045	-3.649	0.000	0.569
AMBD2	-0.163	0.045	-3.649	0.000	0.567
ST1SP	-0.007	0.004	-1.872	0.061	34.670
ST2SP	-0.007	0.004	-1.872	0.061	34.868
Log(ADV)	1.236	0.049	25.310	0.000	10.134

Note: RLC = Red light camera present (yes =1, no = 0), NTR = No turn on right, NLT = No left turn, LTA = Left turn allowed, DEDRTL = Dedicated right turn lane (yes = 1, No = 0), SWLK = Sidewalk (yes = 1, no = 0), PEDSIG = pedestrian signal (yes =1, no = 0), ST1FLOW =one-way traffic on road 1 (yes = 1, no = 0), ST2FLOW = one way road on road 2 (yes = 1, no = 0), ST1RED = All red time on road 1, ST2RED = All red time on road 2, ST1AMB = amber time on road 1, ST2AMB = Amber time on road 2, ADT = Average annual daily traffic volume.

Table 6.4: Crashes resulting in property damage

Poisson Regression	
Dependent variable	PDO
Weighting variable	None
Number of observations	17271
Log likelihood function	-12193.93
Restricted log likelihood	-13275.24
Chi squared	2162.625
Degrees of freedom	17
Prob[ChiSqd > value] =	.0000000
Chi- squared = 19202.31920 RsqP= .1236	
G - squared = 14662.59647 RsqD= .1285	
Overdispersion tests: g=mu(i):	7.193
Overdispersion tests: g=mu(i)^2:	7.431
Robust (sandwich) estimator used for VC	

Variable	Coefficient	SE	b/St.Er.	P Value	Mean X
CONSTANT	-13.425	0.461	-29.113	0.000	
MONTH	-0.004	0.001	-3.959	0.000	29.000
RLCPRES	0.349	0.060	5.812	0.000	0.029
TOTLTL	0.083	0.020	4.033	0.000	1.640
DEDRTL	0.060	0.030	2.030	0.042	0.446
SWLK	0.109	0.036	3.060	0.002	0.432
SLDMED	-0.073	0.038	-1.902	0.057	0.175
PEDSIG	-0.170	0.041	-4.177	0.000	0.257
NLT	0.080	0.047	1.710	0.087	0.102
NTR	0.036	0.035	1.031	0.302	0.208
SNOW	-0.011	0.010	-1.089	0.276	0.410
PRECIP	0.005	0.006	0.795	0.427	3.645
TOTLN	0.003	0.007	0.482	0.630	8.135
ST1FLOW	-0.154	0.032	-4.867	0.000	0.911
ST2FLOW	-0.154	0.032	-4.867	0.000	0.861
ST1RED	-0.010	0.018	-0.591	0.555	1.552
ST2RED	-0.010	0.018	-0.591	0.555	1.543
AMBD1	-0.127	0.036	-3.525	0.000	0.569
AMBD2	-0.127	0.036	-3.525	0.000	0.567
ST1SP	-0.009	0.003	-3.120	0.002	34.670
ST2SP	-0.009	0.003	-3.120	0.002	34.868
Log(ADV)	1.296	0.041	31.268	0.000	10.134

Note: RLC = Red light camera present (yes =1, no = 0), NTR = No turn on right, NLT = No left turn, LTA = Left turn allowed, DEDRTL = Dedicated right turn lane (yes = 1, No = 0), SWLK = Sidewalk (yes = 1, no = 0), PEDSIG = pedestrian signal (yes =1, no = 0), ST1FLOW =one-way traffic on road 1 (yes = 1, no = 0), ST2FLOW = one way road on road 2 (yes = 1, no = 0), ST1RED = All red time on road 1, ST2RED = All red time on road 2, ST1AMB = amber time on road 1, ST2AMB = Amber time on road 2, ADT = Average annual daily traffic volume.

7. Summary of Findings

The results do not support the conventional wisdom expressed in recent literature and popular press that red light cameras reduce accidents. For example, McGee and Eccles (2003) conclude in their review that, “Most of the various studies and analyses show . . . reductions in angle crashes, with some showing smaller increases in rear-end crashes.” Our findings are more pessimistic, finding no change in angle accidents and large increases in rear-end crashes and many other types of crashes relative to other intersections. We did find a decrease in accidents involving a vehicle turning left and a vehicle on the same roadway, which may have been included as an angle accident in some other studies. However, given that these left turn accidents occur only one third as often as angle accidents, and the fact that we find no benefit from decreasing severity of accidents suggests that there has been no demonstrable benefit from the RLC program in terms of safety. In many ways, the evidence points toward the installation of RLCs as a detriment to safety.

We summarize our findings for the variables that can be reliably interpreted in Table 7.1. We indicate a “ + ” for variables associated with increased accidents, and a “ – ”for those associated with a decrease in accidents. We only report associations with a minimum of a 10 percent significance level. For most types of accidents there is a decreasing trend at all signalized intersections. However, in most cases, we see RLCs associated with an increase in accidents.

Table 7.1: Summary of findings on types of accidents

Variables	Total crashes	Angle accidents	Rear End Slow / Stop	Left turning vehicles in different directions	Sideswipe a vehicle in same direction	Other accidents	Severe injury	Possible injury	Property damage
TREND	-	+	-	-	+	-	-	-	-
RLC	+		+	-	+			+	+
SNOW	-		-		-			-	
PRECIP	+		+	+			+		

Some of these findings, particularly that of a strong increase in rear-end collisions, is in accordance with our expectations. We had expected that upon seeing the signs for red light cameras, drivers may panic and try to stop, thus increasing rear-end collisions. The failure of a reduction in severe or angle accidents comes as somewhat of a surprise.

Besides the effect of red light cameras, we should recap the effects of the other control variables used in the study. Precipitation was generally found to increase accidents, while snow was generally related to a decrease through its impact on traffic in southern cities. Various road signs and road characteristics generally associated positively with accidents at signalized intersections include no turn on red and no-left-turn traffic signs. Similarly, longer all-red time is positively associated with some types of accidents. In addition, it can be seen that the number of left-turn lanes is associated with larger accident rates, as are solid medians and dedicated right-turn lanes for some types of accidents. As previously noted in section 4.2, these are likely the result of efforts of GDOT officials to mitigate accidents at accident-prone locations prior to the period of this study. In other words, because there were few changes in these variables at intersections during the study[15], these estimates cannot be taken to be causal in nature. Our results also support previous research showing that longer amber times are associated with reductions in accidents.

Consistently, the results show the positive relationship between traffic volume and accidents. This result is expected since traffic volume is basically an exposure rate, measuring the number of chances for accidents to occur. It is interesting to note whether or not this chance increases one-to-one with traffic volume or less so. Sideswipes and rear-end accidents occurred at an increasing rate as traffic volume increased, as did C injuries and PDO accidents. Some left turning accidents and "Other" accident rates declined as volume increased, possibly due to higher volume roadways reducing actual travel speed or increased driver diligence at heavily-traveled intersections.

At a minimum, we can say that *there is no evidence that the RLC program is decreasing accidents*. Additionally, the data shows that the sites with RLCs are not benefiting from the overall decreasing trend in accidents in Greensboro. There appears to be an increase in most types of accidents that correlates with the placement of a RLC at an intersection. This is surprising, given that regression to the mean bias usually causes a natural decrease in accident rates at locations chosen for a treatment such as a RLC.

Because this is not a randomized trial, there is no certainty of a cause/effect relationship at work. However, the weight of the evidence points away from any conclusion of Greensboro's RLC program increasing safety. We encourage others to perform additional, *careful* research in this area to confirm or contradict these results. As we have seen, simply looking at before and after statistics focusing on RLC sites will tell an incomplete and inaccurate story.

[15] We focused on using intersections that had no major restructuring during the study time period. This allowed the study to focus on the changes due to RLCs.

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APPENDIX A

Analysis of Retting and Kyrychenko's results

As described in Retting and Kyrychenko (2002):

> *A generalized linear regression model was developed to evaluate changes in total crashes, injury crashes, and specific crash types. The model used the natural logarithm of crash counts as the response variable. Independent variables were city, intersection type (signalized and nonsignalized), and period (before and after enforcement). Two-factor interactions of City x Period and City x Intersection Type also were included, because crash trends were different in different cities. Analysis of variance was used to test the statistical significance.*
>
> *Table 1 summarizes changes in the numbers of crashes from the baseline period through the enforcement period, for signalized and nonsignalized intersections. For the three control cities, the frequency of crashes changed in a roughly similar manner at both signalized and nonsignalized intersections. In Bakersfield and Santa Barbara, the number of crashes declined at both types of intersections; in San Bernardino, it increased. Table 1 also summarizes the effect of red light camera enforcement as evaluated by the model. We estimate that red light camera enforcement would reduce the number of crashes at signalized intersections in Oxnard by 7 % (95% confidence interval [CI]=1.3,12.5).*
> *(Page 1823)*

On the next page, in Table A.1, is the data as given in the Retting and Kyrychenko (2001) paper, along with dummy variables described earlier. In addition, each of the 16 observations is given a symbol (a through p) to simplify the equations that follow.

Using the 12 dummy variables, along with a column of ones to represent the regression constant as the independent variable matrix, "X", and the natural logarithm of the crash counts (represented by letters a-p) as the independent variable vector, we derived the formulas for the coefficient estimates (Betas) in terms of the independent variables by using the least squares formula:

$$B = (X'X)^{-1} X'Y$$

The formulas for the regression coefficients are represented algebraically in Table A.2. Representing them in this way allows one to see how the various data used do (or do not) interact in calculating the coefficients. Clearly, the other three cities' data have no impact on the coefficient for the presence of the red light camera (denoted by Camera? in the table).

Table A.1: Data used in replicating Retting and Kyrychenko (2002)

Symbol				Count	Log(count)	Cam?	Bakers	Sbern	Sbarb	Sig?	Bef.	BakBef	SBernBef	BakSig	SBernSig	SBarbSig	SBarbBef
a	before	ns	Bakers	760	6.63332	0	1	0	0	0	1	1	0	0	0	0	0
b		S		771	6.64769	0	1	0	0	1	1	1	0	1	0	0	0
c		ns	Sbern	1220	7.10661	0	0	1	0	0	1	0	1	0	0	0	0
d		s		1324	7.18841	0	0	1	0	1	1	0	1	0	1	0	0
e		ns	Sbarb	712	6.56808	0	0	0	1	0	1	0	0	0	0	0	1
f		s		488	6.19032	0	0	0	1	1	1	0	0	0	0	1	1
g		ns	Oxnard	994	6.90174	0	0	0	0	0	1	0	0	0	0	0	0
h		s		1322	7.1869	0	0	0	0	1	1	0	0	0	0	0	0
i	After	ns	Bakers	753	6.62407	0	1	0	0	0	0	0	0	0	0	0	0
j		s		739	6.6053	0	1	0	0	1	0	0	0	1	0	0	0
k		ns	Sbern	1283	7.15696	0	0	1	0	0	0	0	0	0	0	0	0
l		s		1400	7.24423	0	0	1	0	1	0	0	0	0	1	0	0
m		ns	Sbarb	622	6.43294	0	0	0	1	0	0	0	0	0	0	0	0
n		s		438	6.08222	0	0	0	1	1	0	0	0	0	0	1	0
o		ns	Oxnard	1011	6.9187	0	0	0	0	0	0	0	0	0	0	0	0
p		s		1250	7.1309	1	0	0	0	1	0	0	0	0	0	0	0

Table A.2: Regression coefficients as functions of the dependent variables, i.e. natural logarithms of crash counts

Camera?	$g - o + p - h$
Bakersfield	$\frac{1}{4}a + \frac{3}{4}i - \frac{1}{4}b + \frac{1}{4}j - o$
SanBernadino	$-\frac{1}{4}d - o + \frac{1}{4}l + \frac{3}{4}k + \frac{1}{4}c$
SantaBarbara	$-\frac{1}{4}f - o + \frac{1}{4}e + \frac{1}{4}n + \frac{3}{4}m$
Signalized?	$-g + h$
Before	$g - o$
Bak*Bef	$-g + \frac{1}{2}a - \frac{1}{2}i + \frac{1}{2}b - \frac{1}{2}j + o$
SBern*Bef	$-g + \frac{1}{2}d + o - \frac{1}{2}l - \frac{1}{2}k + \frac{1}{2}c$
Bak*Sig	$-\frac{1}{2}a + \frac{1}{2}b + g - h - \frac{1}{2}i + \frac{1}{2}j$
SBern*Sig	$-\frac{1}{2}c + \frac{1}{2}d + g - h - \frac{1}{2}k + \frac{1}{2}l$
SBarb*Sig	$-\frac{1}{2}e + \frac{1}{2}f + g - h - \frac{1}{2}m + \frac{1}{2}n$
SBard*Bef	$\frac{1}{2}f - g + o + \frac{1}{2}e - \frac{1}{2}n - \frac{1}{2}m$
Constant	o

APPENDIX B

Additional Models Tested for Robustness and Consistency Checks

The authors checked many other possible model formulations and possible confounders. Though the estimates and details changed under each model, the overall conclusions discussed in this report were robust to many different specifications. Below is a partial list of these models.

A) We ran many different models checking for various nonlinear trend functions. We allowed for curved trends, a slope and intercept shifter when the RLC program began (testing for spillovers), and slope and intercept shifters at the RLC sites only. None of these showed an interesting relationship changing the overall results.

B) We corrected for overdispersion in several ways. The statistical significance of the key variables was unchanged.

C) Because the 303 intersections include some with very low traffic volume, we ran the models restricting the observations to those with ADV similar to the RLC sites (between 29,000 and 63,000). The only substantial effect was that using this sample, RLCs were statistically significantly associated with in increase in angle accidents.

D) During the period of study, North Carolina restricted the driving privileges of teenagers so that they could not carry more than one other unrelated person under 21 in the vehicle. This went into effect in December 2002 and appeared to have no effect on the data when we included it as a variable.

E) We ran fixed effects models dropping the intersection characteristics, since there was so little within site variation. The overall results remained unchanged.